

A complex systems perspective on land-use dynamics in the Amazon: patterns, agents, networks

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von

Finn Müller-Hansen, MSc.

Präsidentin der Humboldt-Universität zu Berlin:

Prof. Dr.-Ing. Dr. Sabine Kunst

Dekan der Mathematisch-Naturwissenschaftlichen Fakultät:

Prof. Dr. Elmar Kulke

Gutachter:

1. Prof. Dr. Dr. h.c. mult. Jürgen Kurths
2. Manoel F. Cardoso, PhD
3. Prof. Dr. Holger Kantz

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*This work is dedicated to the peoples of the Amazon, fighting for their traditional lives.
Even if they are not visible in this work, they have not been forgotten.*

Abstract

This thesis investigates how to model and analyze human-nature interactions using the example of deforestation and land-use change in the Brazilian Amazon. Deforestation of tropical rainforests remains a huge threat to biodiversity, local weather patterns, and global climate. I approach this topic from a complex systems point of view, using concepts from theoretical physics and network analysis to guide data analyses of land-use changes and design models of deforestation dynamics.

The thesis is divided into three main parts. The first part reviews modeling approaches to human decision making and behavior. I discuss differences in the underlying assumptions and theories of approaches in three categories: individual decision making and behavior, social interaction, and aggregation of agent behavior and interactions. I give an overview of how these approaches are used in agent-based and land-use models. A main conclusion of this review is that no single modeling approach captures all relevant aspects of human behavior. Instead, modelers have to choose the appropriate approaches by taking into account the type of agent, the suitability of the underlying behavioral theory to the context of decision making, and the spatial and temporal scales that are relevant for the research questions and the model purpose.

The second part of the thesis combines Markov-chain and cluster analyses to detect patterns in satellite-derived land-cover maps of the Brazilian Amazon. I derive transition rates between different land-cover types for various subregions and apply cluster analysis and community detection algorithms to find spatial patterns of land-cover dynamics. The analysis reveals the spatial and temporal heterogeneity of land-cover transitions and shows that neighboring subregions tend to undergo similar transitions. The resulting patterns can be linked to and thus complement local studies of land-cover dynamics in the Brazilian Amazon. Finally, I use the obtained transition rates to parameterize simple Markov-chain models and compute land-cover projections.

The third part develops an agent-based model to investigate under which conditions the intensification of cattle ranching can reduce deforestation in the Amazon. Cattle ranching is the main direct driver of deforestation in the region and its intensification has been proposed but also highly debated as an anti-deforestation measure. The model captures stylized environmental, economic, as well as social processes, and uses heuristics representing extensive or semi-intensive land management strategies to describe agent decision making. I present a detailed analysis of the non-linear transient model behavior. Fast intensification can only lower deforestation rates if local cattle markets saturate. Under other environmental and economic conditions intensification does not reduce deforestation rates and may even increase deforestation.

The contributions of this thesis are a demonstration that a combination of modeling tools from complexity science and social-science theories of human decision making is needed to study emergent dynamics of social-ecological systems. To understand such systems is a main prerequisite for designing effective policies that foster a more sustainable management of these systems. I conclude by suggesting domains for further research to approach this goal.

Zusammenfassung

Die vorliegende Doktorarbeit untersucht, wie sich Mensch-Umwelt-Interaktionen am Beispiel der Abholzung und Landnutzungsänderung im Amazonas modellieren und analysieren lassen. Die Abholzung tropischer Regenwälder ist eine große Bedrohung für Biodiversität, lokale Wettergeschehen und das globale Klima. Hier nähere ich mich dem Thema, indem ich Landnutzung aus der Perspektive komplexer Systeme betrachte. Konzepte der theoretischen Physik und Netzwerkanalyse ermöglichen es, Daten zu analysieren und Modelle zu entwickeln, die die Dynamik der Abholzung fassen können.

Die Arbeit ist in drei Hauptteile gegliedert. Im ersten Teil gebe ich einen detaillierten, kritischen Überblick über Modellansätze um Entscheidungen und menschliches Verhalten zu beschreiben und diskutiere deren zugrundeliegende Annahmen. Die Ansätze werden in drei Kategorien eingeteilt: individuelle Entscheidungen und individuelles Verhalten; soziale Interaktionen zwischen Akteuren; und Techniken um das Verhalten individueller Akteure und deren Interaktionen zu aggregieren. Ich diskutiere außerdem Beispiele für Anwendungen dieser Ansätze in agentenbasierten Modellen und Landnutzungsmodellen. Der Review kommt zu dem Schluss, dass es keinen Ansatz gibt, der alle relevanten Aspekte menschlichen Verhaltens abbilden kann. Um einen geeigneten Ansatz zwischen den aufgezeigten Optionen auszuwählen, müssen folgende Aspekte berücksichtigt werden: der Akteurstypus, die Eignung der zugrundeliegenden Verhaltenstheorie für den Entscheidungskontext, und die zeitlichen und räumlichen Skalen, die für die Forschungsfrage und den Modellzweck entscheidend sind.

Der zweite Teil der Arbeit kombiniert die Theorie von Markow-Ketten mit Clusteranalysen um Muster in satellitengestützten Landbedeckungsdaten im brasilianischen Amazonas zu identifizieren. Für unterschiedliche Teilgebiete bestimme ich Übergangsraten zwischen verschiedenen Arten der Landbedeckung und vergleiche diese mit Clusteranalysen. Ziel ist die Identifikation von räumlichen Mustern. Die Analyse macht die räumliche und zeitliche Heterogenität von Übergängen deutlich und zeigt, dass für angrenzende Teilgebiete ähnliche Übergänge festzustellen sind. Die identifizierten Muster decken sich mit den Ergebnissen von Studien, die die Dynamik von Landnutzung im Amazonas lokal untersuchen und ergänzen diese Studien daher. Abschließend werden einfache Markow-Modelle mit den gewonnenen Daten parametrisiert um Projektionen für Landbedeckungsanteile zu errechnen. Diese werden untersucht und ihre Aussagekraft diskutiert.

Im dritten Teil entwickle ich ein agentenbasiertes Modell um die Frage zu untersuchen, unter welchen Bedingungen die Intensivierung der Viehhaltung im Amazonas die Abholzung reduzieren kann. Rinderhaltung ist der wichtigste unmittelbare Treiber von Abholzung in der Region. Um die Abholzung einzudämmen, wird eine Intensivierung der Rinderhaltung als politische Maßnahme vorgeschlagen, gleichzeitig aber auch scharf kritisiert. Um die Wirkung einer Intensivierung zu untersuchen, verbindet das Modell vereinfachte ökologische, ökonomische und soziale Prozesse und wendet Heuristiken an, um extensive und semi-intensive Landnutzungsstrategien der Viehhalter abzubilden. Das Modell weist nichtlineare, transiente Dynamiken auf. Eine detaillierte Analyse des Modells zeigt, dass eine Intensivierung die Abholzungsraten nur dann verringern

kann, wenn der lokale Viehmarkt saturiert. Unter anderen ökologischen und ökonomischen Bedingungen wird die Abholzung durch eine stärkere Intensivierung nicht verringert und kann die Abholzung sogar erhöhen.

Die Ergebnisse dieser Arbeit demonstrieren, dass eine Kombination aus Modellierungsansätzen aus der Theorie komplexer System einerseits und sozialwissenschaftlichen Theorien menschlicher Entscheidungen andererseits gebraucht wird, um die emergente Dynamik sozial-ökologischer Systeme zu untersuchen. Ein besseres Verständnis solcher Systeme ist eine Grundvoraussetzung um effektive Politikmaßnahmen zu entwickeln, die eine nachhaltigere Bewirtschaftung des brasilianischen Amazons und anderer sozial-ökologischer Systeme fördern. Die Arbeit schließt mit Vorschlägen für weiterführende Forschungen, um diesem Ziel näherzukommen.

List of publications

This dissertation is partly based on the following publications. The identifiers P₁ - P₆ are cited in the text to highlight passages that are connected to these papers. The dissertation partly uses passages from the papers that were written by the author of this thesis. All passages provided by my co-authors were thoroughly rewritten.

- P₁ **F. Müller-Hansen**, M. Schlüter, M. Mäs, J. F. Donges, J. J. Kolb, K. Thonicke, and J. Heitzig (2017). Towards representing human behavior and decision making in Earth system models – an overview of techniques and approaches. *Earth System Dynamics* 8, 977-1007. DOI: 10.5194/esd-8-977-2017.
- P₂ J. F. Donges, W. Lucht, **F. Müller-Hansen**, and W. Steffen (2017). The technosphere in Earth System analysis: A coevolutionary perspective. *The Anthropocene Review* 4(1), 23-33. DOI: 10.1177/2053019616676608.
- P₃ **F. Müller-Hansen**, M. F. Cardoso, E. L. Dalla-Nora, J. F. Donges, J. Heitzig, J. Kurths, and K. Thonicke (2017). A matrix clustering method to explore patterns of land-cover transitions in satellite-derived maps of the Brazilian Amazon. *Nonlinear Processes in Geophysics*, 24, 113-123. DOI: 10.5194/npg-24-113-2017.
- P₄ **F. Müller-Hansen**, J. Heitzig, J. F. Donges, M. F. Cardoso, E. L. Dalla-Nora, P. Andrade, J. Kurths, and K. Thonicke (submitted). The dynamics of Amazon deforestation and cattle ranching intensification: insights from an agent-based social-ecological model. Submitted to *Ecological Economics*.
- P₅ C. Ciemer, N. Boers, M. Hirota, J. Kurths, **F. Müller-Hansen**, R. S. Oliveira, and R. Winkelmann (in review). Tropical vegetation with higher rainfall variability is more resilient to climate change. In review for *Nature Geoscience*.
- P₆ J.F. Donges, J. Heitzig, W. Barfuss, J. A. Kassel, T. Kittel, J. J. Kolb, T. Kolster, **F. Müller-Hansen**, I. M. Otto, M. Wiedermann, K. B. Zimmerer, and W. Lucht (2018). Earth system modelling with complex dynamic human societies: the copan:CORE World-Earth modeling framework, *Earth System Dynamics Discussions*, in review. DOI: 10.5194/esd-2017-126

Berlin, March 29, 2018

Preface

This thesis presents the work of a physicist venturing into the fields of economics, social ecology, and geography to better understand local impacts of our current socioeconomic system. It is an interdisciplinary endeavor to contribute to solutions for one of the biggest challenges of our time:

How can we transform the globally dominating production and consumption systems such that they provide the human population with basic needs for a good life while not exceeding the ecological limits of the planet?

Driven by this question, I have embarked on many journeys, both intellectually and physically, to arrive at the results and views presented in this thesis. Before jumping into the topics of this thesis, I want to share some experiences that I was privileged to make during the research stays in Brazil, made possible through my graduate program (International Research Training Group 1740: *Dynamical Phenomena in Complex Networks*).

When I first traveled the road between São Paulo and Rio de Janeiro to the National Space Institute of Brazil that I would work in, I found myself questioning how the landscape around me might have looked before it was put to agricultural use. It was hard to imagine. Why is it that we only start thinking about such questions when confronted with unknown lands or with a culture that is at least partly unknown to us? The same question could be asked for European landscapes. However, in Brazil the formation of the cultural landscape in the form that we see today happened more recently. The road from São Paulo to Rio de Janeiro passes through the Paraíba valley, which is part of the Atlantic forest ecoregions and was once covered by a beautiful dense forest. Only 5% of the original area of this type of forest remains, mostly on the sloppy hills of the Costa Verde (green coast), where the productive use of land is hardly practicable. Seeing all those pastures partly degraded, covered with termite hills, sometimes grazed by white cows, I asked myself: Is this how the Amazon will look like in the future? In a few decades, if the deforestation in the Amazon does not slow down, would all Amazon rainforest be replaced by a similar landscape?

The landscape made me sad. Not because it was not pretty. In some parts, the Paraíba valley is very pretty, especially around Cachoeira Paulista, the city of my hosting institute. The landscape made me sad, because I knew what was there before. I could see this from the small remains of forest patches seaming the creeks and covering the steep slopes.

During my third stay in Brazil, I read a book that helped me better understand this sensation. Levi-Strauss made several journeys through Brazil from the 1930s to

the 1950s. He published his philosophical, anthropological, and sociological account of and thoughts about these journeys in his book “Tristes Tropiques” (Sad Tropics).

He wrote about the landscapes surrounding São Paulo, where once the coffee barons that made São Paulo rich had their plantations:

Erosion had done much to ravage the country before me; but above all Man was responsible for its chaotic appearance. Originally it had been dug and cultivated; but after a few years continual rain and the exhaustion of the soil made it impossible to keep the coffee-plantations in being. They were therefore moved to an area where the soil was fresher and more fertile. [...]

Here in Brazil the soil had been first violated, then destroyed. Agriculture had been a matter of looting for quick profits. Within a hundred years, in fact, the pioneers had worked their way like a slow fire across the State of São Paulo, eating into virgin territory on the one side, leaving nothing but exhausted fallow land on the other. [...]

To the European traveller, this is a disconcerting, because an unclassifiable, landscape.¹

Did society learn from past experience to avoid such developments in the Amazon?

What I also did during my third stay was to finally travel to the Brazilian Amazon. The main destination of the journey was Manaus, the megacity inside the rainforest at the junction where the Rio Negro meets the Amazon river. From there, I went to an excursion to a measurement site about two hundred kilometers north inside the rainforest, the ATTO tower.

Two insights became especially tangible on this journey: First, the idea that the Amazon is a monotonous landscape covered by homogeneous forest is wrong. It is actually very diverse: wide lowlands are interrupted by hilly or even mountainous regions, the forest changes from wet forests along the rivers to dry forest on the hills with very different plant species. Second, the idea of untouched ecosystems of the Amazon is at least misleading. The road to the ATTO tower went through dense forest, but also passed areas that had been cleared to make room for pastures and plantations. Along the river that we navigated to get closer to the tower, there were small communities living a modest life. From down here, the forest, which seemed deserted on the satellite images that I had studied, was actually home to many people living from and with it. The landscapes of the Amazon basin have always given home to indigenous people who left their traces in the landscape. Think for example of the Terra Preta, a very fertile anthropogenic soil found in many areas in the Amazon. However, the interference with the ecosystems has never been on a comparable scale of what we see today.

The real impact of deforestation is visible from the airplane going south from Manaus to Brasília: The flight starts over a sea of green forest, in which Manaus

¹ Cited from Lévi-Strauss, C. (1961 [1955]): *Tristes Tropiques*, English translation by John Russell, Criterion Books, New York, pp. 97-98.

is situated. Then, first patches of lighter green and brown appear, marking the first signs that modern civilization nibbles at the forest. Roads appear that divide the nearly endless sea by cutting through it and that are sometimes so unnaturally straight that the scenery could be an abstract painting. Finally, the forest dissolves more and more into large agricultural landscapes with ranches, farms, roads, and villages becoming denser and denser. In these areas, the major land-cover changes that I study in this thesis have already taken place.

So what drove this research from the beginning was a curiosity to understand what type of dynamics are driving this massive transformation of the surface of the Earth. The thesis that you have in front of you is my attempt to understand at least some aspects of the ongoing land-use changes in the Amazon from a complex systems' point of view, that is, focusing on dynamic interactions of the systems' constituents by using some of the tools which my education in physics provided me with. To do so, I integrated insights from different disciplines and applied methods from statistical physics to shed light on the complex interaction between social and environmental dynamics in the land system. I worked together with scientists from the natural and social sciences, which has been both an exciting learning process and, sometimes, a challenge. It showed me that one discipline alone cannot possibly tackle these questions.

Last but not least, I want to point out that deforestation of the global rainforests and its underlying drivers remains an important political issue that urgently needs solutions. Otherwise these impressive ecosystems will be lost and many landscapes of the Amazon will soon look similar to the one around Cachoeira Paulista.

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I want to thank a number of people who accompanied me on this journey and without whom this thesis would not have been written.

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I hope that the collaborations continue!

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Chapter 1.

Introduction

“The methods of theoretical physics should be applicable to all those branches of thought in which the essential features are expressible with numbers.”

- Paul A. M. Dirac at the Nobel Banquet in Stockholm, 1933

1.1. Theories and models of complex systems

Physicists have been fascinated by complex systems for a long time. This started with the development of statistical mechanics and its successful explanation of thermodynamic properties of gases. Today, concepts from theoretical physics are applied to various complex systems, ranging from the collective motion of animals (Vicsek and Zafeiris, 2012; Romanczuk et al., 2012) to neural networks (Peretto, 1984; Ermentrout, 1998). With the availability of increasing computing power, analytical methods are complemented by numerical simulations that help explaining how complex systems work. These methods are increasingly applied to social and social-ecological systems.

This thesis applies such methods to investigate a topic that seems to be far away from classical physics: land-use change and its underlying drivers. This introductory section explains the various connections. I start introducing the basic terminology and concepts from complex systems theory, discuss how they are related to concepts in theoretical physics, and motivate why they are useful to describe many aspects of social and social-ecological systems.

Complex systems are collections of interdependent entities that interact, i. e., that mutually influence each others' properties. The entities can belong to the same category but also to different categories, often being heterogeneous regarding some of their properties. Entities themselves can be composed of lower-level entities making up a sub-system. Complex systems theory is not a unified theory but rather a conglomerate of different approaches like cybernetics, dynamical systems theory, chaos theory, information theory, and network theory. It has been developed by scientists from different disciplines to better understand systems like simple organisms, the brain, ecosystems, societies, and the planet Earth. Because of the different disciplines and applications, there are different accounts of complexity (Adami, 2002). In the following, I will give a short overview of characteristic properties usually associated with complex systems.

Complex systems are characterized by nonlinear behavior, often arising from feedback loops between the system's components. This can lead to emergent² dynamics, i. e., behavior at the system level that is qualitatively different from the behavior of its constituents and often a result of multi-level interactions. Complex systems can show self-organization, which is the formation of ordered and robust patterns at the system level originating from local interactions (Prokopenko, Boschetti, and Ryan, 2009). They can also be adaptive, meaning that they alter their functionality to cope with changed environmental conditions.

Methods and approaches from statistical physics can systematically characterize complex systems. On the one hand, statistical methods allow systematically characterizing the empirical properties of complex systems. For example, information theory has been used to measure the statistical complexity of a system on a scale, on which ordered and random systems are two extreme cases with low complexity (Crutchfield and Young, 1989). On the other hand, mathematical modeling techniques are used to develop a better understanding of the mechanisms and processes leading to the above-mentioned characteristics. Models capture the multiple interactions of entities as well as their dynamical properties in a formal and unambiguous way. Thereby, they help to systematize knowledge gained in empirical research. Many complex systems can be described for example by network structures, in which nodes represent entities or subsystems, and links are associated with interactions. The network structures are formalized as graphs and can be evaluated statistically (Sayama et al., 2013).

Physical theories are often formalized in the form of models, which is why the model tends to be regarded as an exact description of nature. This rarely applies to models of complex systems, which often require simplifications or abstractions. Researchers constructing models of complex systems are therefore faced with the decision, which entities, processes, and properties of the system to include in a model and which ones to leave out (O'Sullivan, 2004). In the following, I outline approaches to deal with these challenges.

It is often not needed to describe the real-world system in a model in as many aspects as possible and may even be counterproductive for developing meaningful models. On the contrary, a guiding principle for model composition is to strive for simplicity: models should only comprise those entities and processes that are necessary to give rise to the phenomenon that is to be explained. This principle has been discussed as a guideline to choose between scientific hypothesis and is known as Occam's razor.

Stylized models of complex systems try to simplify the systems as much as possible and represent it by collections of (often similar) elements coupled by few processes and depending on a limited number of parameters. The simplifications and abstractions from many details immediately raise the question: How do stylized models relate to

²I use the notion of emergence here in the weak understanding of the word, which refers to system-level phenomena that are qualitatively different from their underlying local-level dynamics but nevertheless can arise from interactions of the systems' constituents. This weak notion can be contrasted by a strong understanding of emergence, which embraces the irreducibility of system-level phenomena to lower-level dynamics. For a discussion see Bedau (1997).

the described real-world system and how is it possible to learn something from such models?

This question has been explored in philosophical and methodological discussions on modeling, especially in the social sciences (Morgan and Knuuttila, 2012). One understanding is that models are formalized thought experiments that allow the conceptual exploration of different possibilities in a system (e.g., Hausman, 1992). Such accounts of models highlight their constructed quality and therefore can hardly explain their connection to the real world. There are other accounts that describe modeling as the process of isolating particular elements of a system to study their representations in isolation (Mäki, 1992). Sugden (2000) suggests understanding stylized models as ‘credible worlds’ rather than simplifications of the real world. In this understanding, a model’s credibility derives from its ability to describe what could have been true in the real world, similar to the plot of a realist novel. Likewise, Mäki (2009) describes models as credible surrogate systems. Similar considerations can be made about the implementation of models for simulations (Grüne-Yanoff and Weirich, 2010). All these accounts of stylized models help to understand why models (of complex systems) can provide new insights even if and sometimes only because they are false (in the sense that they make simplifying assumptions about the described system, see Wimsatt, 1987; Mäki, 2011). In contrast to models aimed at quantitative predictions or scenario development, stylized models thus have the purpose to explore dynamical properties of an abstraction of the real-world system and its dependency on external parameters with the aim of generating qualitative insights on how the real-world system works.

Stylized modeling and statistical analysis cannot only be applied to complex natural systems, but may also help to understand social or social-ecological systems (Cilliers, 2000; Castellano, Fortunato, and Loreto, 2009; Page, 2015). Modeling of social systems calls for stylized models because it is impossible to consider the heterogeneity of agents of a social system in all relevant aspects. In many real-life settings, simple models of social mechanisms can be good descriptions of key features of the dynamics at work.

However, complex system involving human and social agents are very different from purely ecological or physical systems because they are shaped by human decision making, strategic interaction, and the resulting adaptive behavior. Such systems have also been termed complex adaptive systems (Levin et al., 2013). Because there is no unified theory that captures all particularities and indeterminacies of human behavior, models including humans have to thoroughly account for the specificity of a decision situation and the limitation of the used approaches. Furthermore, social-ecological systems are often characterized by feedback loops between human actions and the response of the natural environment (Donges et al., 2017b). These interactions between social and ecological subsystems in turn can lead to the adaptation of the agents’ behavior, which is why already simple fully coupled models exhibit complex dynamics (Levin, 1998; Palmer and Smith, 2014).

Because of these specificities of social systems, this thesis includes a thorough review of approaches that allow modeling human decision making in the context

of social-ecological systems. Some of the reviewed approaches are then applied to investigate interdisciplinary research questions related to deforestation and land-use change. In the following, I describe how a complex systems perspective can contribute to a better understanding of land-use systems.

1.2. Land use as a complex social-ecological system

Land use can be considered one of the most important dimensions of human interaction with the natural Earth system. Land use is the second most important driver of climate change besides fossil fuel combustion in the energy sector. It accounts for around one quarter of global emissions (24% of CO₂ equivalents, see Fig. 1.1 and Victor et al., 2014). The emissions from land-use change stem to a large extent from deforestation, especially in tropical ecosystems (Smith et al., 2014). Apart from their interaction with the atmosphere, land-use systems play an important role for biodiversity, water and nutrient cycles, and other dimensions of global change (Foley et al., 2005). Replacement of natural ecosystems with mono-culture farming strongly reduces species diversity on the land. Irrigation systems and the utilization of fertilizers alter the water and nutrient flows through the environment and thus the fertility of the land. Because the provision with food and other essential goods depends crucially on the integrity of the natural and agricultural ecosystems on land, such changes in natural cycles have in turn potentially severe impacts on human societies. Driven by demand for food, fiber, biofuels, and other agricultural products, land is converted to agricultural areas if it is easily accessible and land prices are low (Lambin and Meyfroidt, 2011). Furthermore, uncertain land tenure can be a factor promoting deforestation because it signals appropriation of an area.

A complex systems perspective accounts for the following characteristics of land-use systems. First, there is a huge heterogeneity between cultural and climatic regions, each having regional specificities at various levels from single land-use practices to

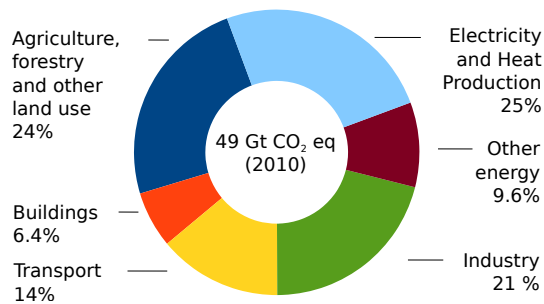


Figure 1.1.: Share of different sectors to global greenhouse gas emissions in terms of CO₂ equivalents in 2010. Adapted from Victor et al. (2014), Fig. 1.3.

1.2. Land use as a complex social-ecological system

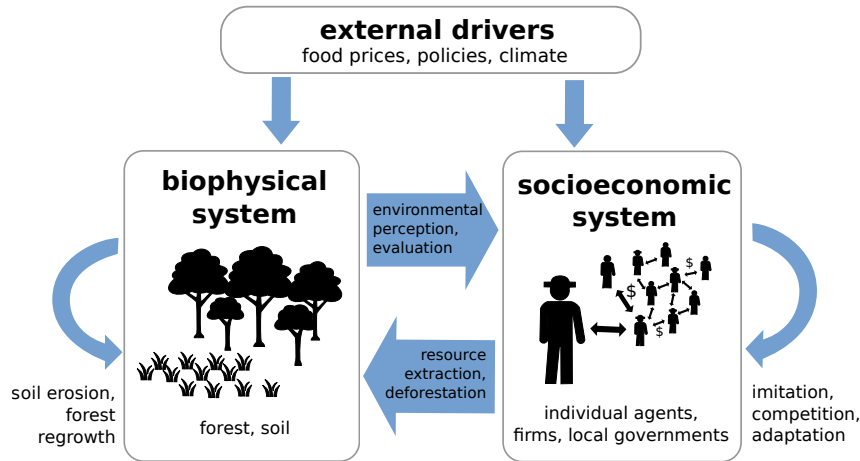


Figure 1.2.: Illustration of human-nature interaction in the land-use context.

general land-cover and land-use³ change patterns. Second, many land-use systems are organized in a decentral way and are characterized by a huge variety of partially independent and uncoordinated actors. These actors may be connected through different markets that range from local to global levels of integration. Third, land-use practices are strongly determined by social driving forces, such as traditions and cultural norms, even though – depending on the agents – economic considerations may also play an important role. Figure 1.2 shows an illustration of some of the multiple human-nature interactions in land-use systems.

A complex systems perspective on land use can therefore generate insights not captured by approaches that either only focus on the social or the natural subsystems or only consider one-way interactions (Verburg et al., 2015; Brown, Brown, and Rounsevell, 2016). For example, climate change will likely affect land use in two different ways: First, the changing climate will have a direct impact on harvests as many regions will experience higher temperatures and more severe droughts. This will influence the decisions on future land use. Second, climate change will possibly alter the risk perception of consumers regarding the environment and thereby might change their consumption patterns. Modeling approaches from complex systems science can capture how land-use patterns and changes result from the interaction of environmental and economic processes with collective and individual decision making of different agents in the land system (Brown et al., 2017; Thornton et al., 2017). Furthermore, not accounting for feedback loops between social and natural systems can lead to unintended consequences of policy interventions. Approaches that take feedbacks into account may therefore help to find ways to initiate transformations to a more sustainable management of land-use systems (Mercure et al., 2016).

³In this thesis, I use the general term “land cover” for areas covered with natural vegetation and cultivated areas, whereas “land use” is always associated with human activities.

This thesis focuses on the Brazilian Amazon as a key region of global change. The following section introduces important aspects of deforestation and land use in the region, their interaction with the ecosystems, and the socioeconomic and political setting.

1.3. Deforestation and land-use change in the Brazilian Amazon

The Amazon basin is the most prominent example of human-nature interactions in the land system because it is at the same time a hot-spot of large-scale land-cover change and a key region for global biodiversity (Laurance and Williamson, 2001; Keller et al., 2009; Davidson et al., 2012). The Amazon basin is home to the largest remaining tropical rainforest on the planet. It covers an area larger than the next two largest coherent tropical forests in the Congo basin and in Indonesia together. But it is also a region with very high forest loss over the last decades (Hansen et al., 2013). In the region, unsustainable logging, extraction of fossil and mineral resources, and agricultural expansion of cattle ranching and soy bean cultivation are the main drivers. These economic activities lead to a fragmentation of the forest and thus to biodiversity loss and a destruction of ecosystems (Laurance et al., 2002).

The Amazon is not only threatened by deforestation. Global climate change will probably have a negative impact on Amazon precipitation, leading to an increase in forest fires and possibly to a massive forest dieback (Malhi et al., 2009; Rammig et al., 2010; Chen et al., 2011). Even though the Amazon ecosystems are to a certain extent resilient to changes in climate (Ciemer et al., in review, P5), effects of deforestation and climate combined increase the risk that they are getting destabilized. Furthermore, there are feedbacks between the vegetation and the climate that could constitute a tipping point (Nepstad et al., 2008; Staal et al., 2015): Deforestation beyond a certain limit could induce a runaway dynamic, leading to irreversible large-scale dieback because crucial water cycling through the atmosphere is interrupted by agricultural land use (Zemp et al., 2017a; Zemp et al., 2017b; Boers et al., 2017; Lovejoy and Nobre, 2018).

Fig. 1.3 shows a map of the Amazon region including the hydrological limits of the Amazon basin, which comprises all river catchments contributing to the Amazon river. Furthermore, it shows an approximate boundary of Amazon ecoregions, i. e., ecoregions with similar climate, flora (forest), and fauna. Finally, the map indicates political and legal borders, including the Brazilian legal Amazon, which plays an important role for national monitoring and policy. As you can see in the map, the Brazilian legal Amazon comprises the bigger part of the Amazon basin and ecoregions.

Large-scale deforestation in the Brazilian Amazon started in the 1970s with the authoritarian government promoting settlements in the Amazon and launching massive resettlement and colonization programs (Fearnside, 2005; Rudel, 2007). The role of the government changed beginning in the 1990s, when deforestation was more and more driven by economic activities and national as well as international political

1.3. Deforestation and land-use change in the Brazilian Amazon



Figure 1.3.: Map showing the South American continent with the Amazon basin (blue line), the Amazon ecoregions (green line), the Brazilian legal Amazon (red line) and the border of Brazil (thick black line). Furthermore, the base map shows the extend of the forest in green and indicates the locations of Manaus and São Paulo.

movements campaigned for more forest conservation. This led to the establishment of large conservation areas, while at the same time the government still promoted agricultural development in the region, which implied that private land-owner could legally deforest parts of their property. The decision to fight illegal deforestation required the establishment of a monitoring program to map deforestation activities and to provide a basis for law enforcement.

Deforestation in the Brazilian Amazon is monitored through the PRODES program. Figure 1.4 shows the extent of deforested areas by 2016 and illustrates the spatial pattern of deforestation as discussed in the literature (Becker, 2005): The so-called arc of deforestation, where historically most of the deforestation took place, spans from the southwest to the east of the region. Most of the population of the Brazilian Amazon lives in the arc and the land use is mostly consolidated, meaning that only few changes occur. Current hot spots of deforestation, the frontier regions, are located at the edges of the arc as well as along the main highways that lead into the heart of the rainforest. The further away from the frontiers the regions are, the further they tend to be consolidated. Until today, about one fifth of the Brazilian Amazon has been deforested. This number does not account for forest degradation, which affected

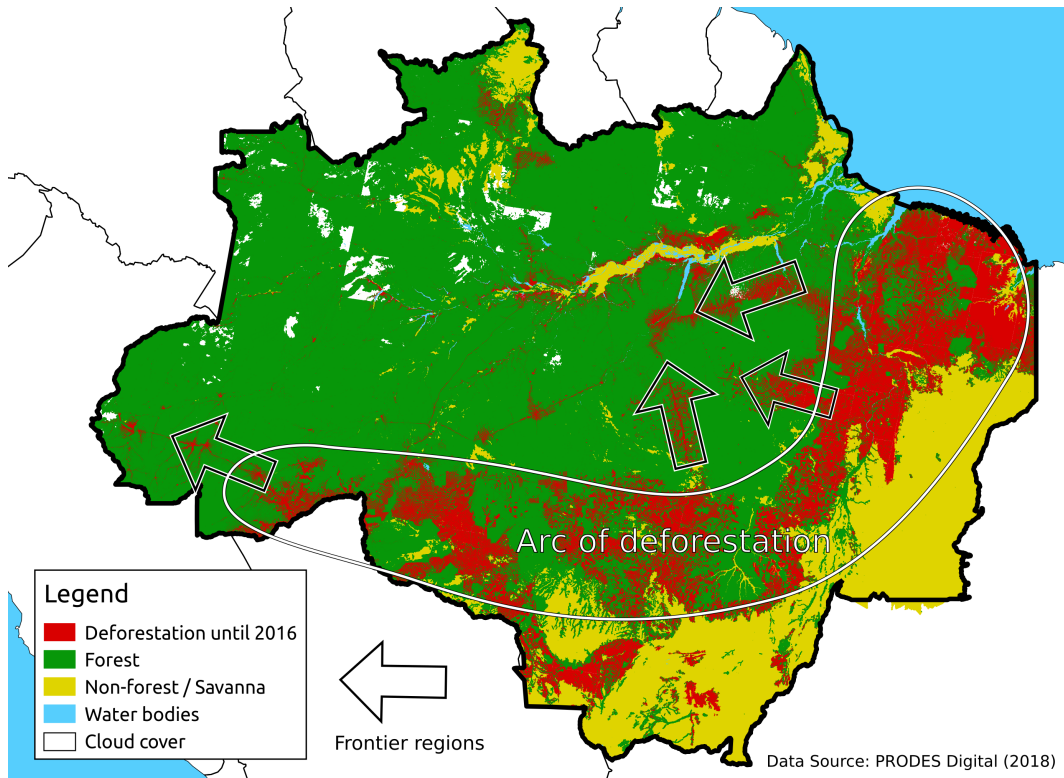


Figure 1.4.: Spatial pattern of deforestation in the Brazilian Amazon: The red areas were deforested between 1970 and 2016. Today, a considerable part of deforestation happens in the frontier regions (black arrows) at the edge of the so-called arc of deforestation (white line). In the arc, the population density is much higher, land tenure gets settled and pasture is increasingly replaced by agricultural land use.

equally large areas as deforestation in the last decade (Tyukavina et al., 2017).

Since large-scale monitoring of deforestation started, the deforestation rates in the Brazilian legal Amazon have undergone strong changes. Figure 1.5 shows the evolution of deforestation rates over the last 30 years. From the late 1990s, deforestation rates fluctuated strongly around a rising trend. But after 2004, a significant decline has been observed, which raised hopes that the rates could tend towards zero deforestation. Since 2012, however, deforestation rates stagnated and fluctuated between 5000 and 8000 km² per year, corresponding to a reduction of 57 to 72% of the average deforestation before 2005. The changes have been explained by a variety of different factors, for example new monitoring programs, public policies and supply chain interventions (Nepstad et al., 2014; Dalla-Nora et al., 2014; Gibbs et al., 2015). In recent years, deforestation rates even rose again. This raises the question about future deforestation in the Amazon: Will the rates decline or resurge?

This question can only be answered when taking the complex interactions of external and internal drivers of deforestation into account.

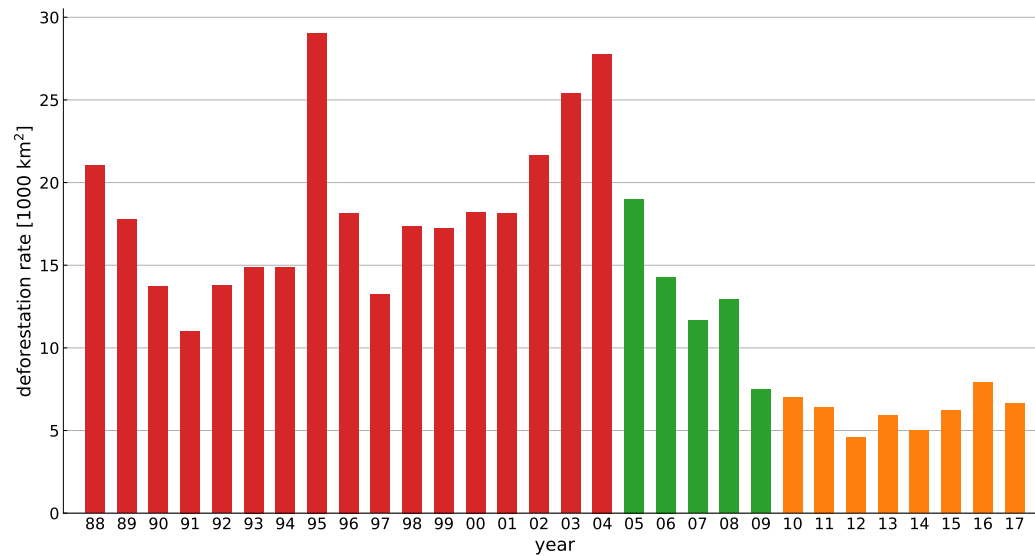


Figure 1.5.: Evolution of deforestation rates in the Brazilian Amazon from 1988 to 2017. The colors indicate three distinct phases. Red: high deforestation rates until 2004 (including considerable fluctuations), green: declining rates in the second half of the 2000s, orange: stabilization or resurgence of deforestation in recent years. Data from PRODES (2018), own coloring.

1.4. Drivers of deforestation and land-use change

In the following, I will shortly discuss two different perspectives on the drivers of Amazon deforestation. The first perspective focuses on the different agents that play a role in the deforestation process, while the second focuses more on external driving factors. Both perspectives include the discussion of endogenous factors or proximate causes (Lambin, Geist, and Lepers, 2003) that are associated with high deforestation rates. Figure 1.6 shows a synthesis of the most important drivers of deforestation and their interdependence.

The agent-centered view on deforestation acknowledges that there are different agent types, often households or agricultural firms, playing specific roles in the deforestation process (Aldrich et al., 2006; Rudel, 2007). The role of agents can also change over the households' life cycle (Walker et al., 2002). Fearnside (2008) describes an agent typology along the following categories: Poor migrants entering the frontier regions often become either land squatters occupying public land, miners that search for gold, or modern slaves that fall into the debt trap and therefore have to provide cheap labor for deforestation activities. Migrants with more endowments become loggers, colonists, capitalized farmers, or ranchers. Last but not least, land grabbers (grileiros) and drug traffickers deforest the land for speculation and money laundering. On the other side, there are conservationists, rubber tappers, and indigenous and

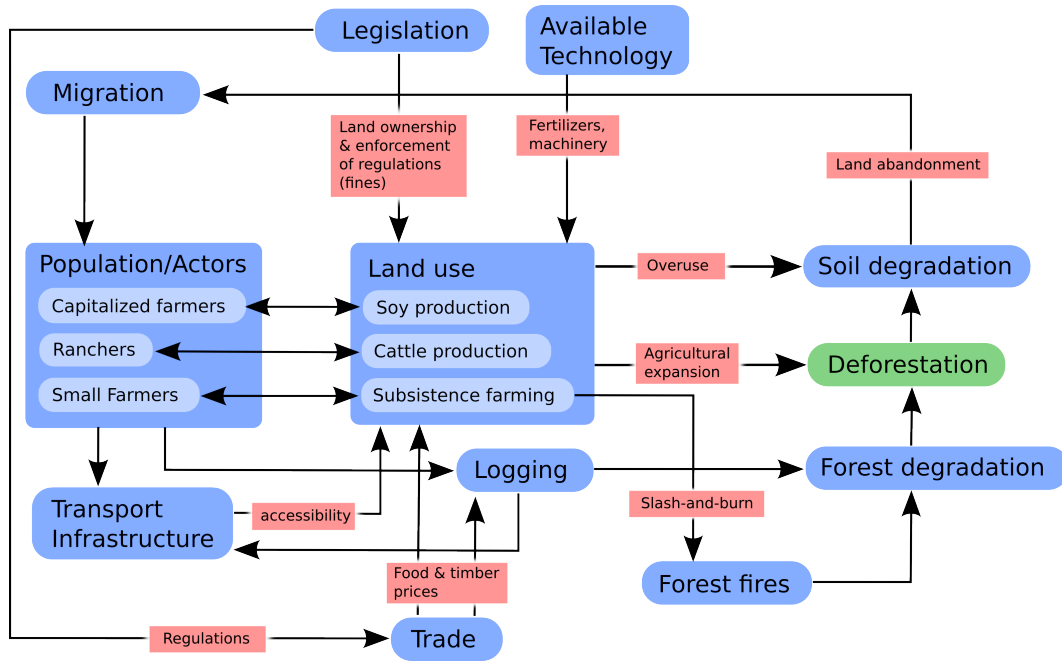


Figure 1.6.: An overview of drivers of deforestation in the Amazon and their interrelations. Compiled from an extensive literature review.

other traditional communities living from the products of the forest that oppose large-scale deforestation.

There are different theories to systematize the agent-driven dynamics of the deforestation frontier focusing on tandems of agent types (Rudel, Bates, and Machinguashi, 2002; Walker, 2004; Parker et al., 2008). The hollow frontier hypothesis proposes that the frontier is first developed by smallholders (mainly low intensity shifting cultivation and/or small-scale cattle ranching). They are then pushed further into the forest as land gets concentrated in the hands of wealthy land owners that use it as pasture for large-scale ranching or buy it for land speculation. The frontier is demographically hollow as the consolidation comes with the out-migration of smallholders. The process of land concentration also drives social stratification (Aldrich et al., 2006).

Clear-cut deforestation for agricultural uses is often preceded by selective logging, i. e., extraction of valuable trunks from the forest, which leads to forest degradation but is usually not classified as deforestation. These often illegal logging activities help to open up the land for land-use activities by building access roads to otherwise hardly reachable areas. This dynamic is sometimes called the invasive forest mobility hypothesis in the literature (Walker, 1993).

The importance of different agent types and the resulting magnitude of deforestation is influenced by external political and economic drivers (Soares-Filho et al., 2006; Barona et al., 2010; Soler et al., 2012; Nepstad et al., 2014). The role of the state for deforestation changed beginning in the 1990s from a strong driver of Amazon

1.5. Outline of the thesis and main research questions

colonization to both a promoter of forest conservation and agricultural development at the same time. A main driver leading to deforestation is the construction of (paved) roads (Perz et al., 2008), which are part of a larger infrastructure to open up the region, including for instance hydroelectric dams. Furthermore, deforestation rates are linked to population density in the respective area (Hargrave and Kis-Katos, 2013; Krüger and Lakes, 2014). Deforestation rates have also been linked to economic factors. For instance, they tend to increase with higher prices for agricultural products and wood (Hargrave and Kis-Katos, 2013).

An important mechanism that externally drives deforestation is indirect land-use change: The expansion of agricultural production into old pasture in other parts of Brazil pushes ranchers out of these areas. This also happens in the south of the Brazilian Amazon, in the state of Mato Grosso, where soy bean cultivation increased strongly. This leads to the displacement of cattle ranching activities into the frontier regions, where most of the clear-cut deforestation is associated to pasture expansion (Barona et al., 2010). Such indirect land-use changes are a considerable driver of the deforestation dynamics. Arima et al. (2011) show that a reduction of soy production on former pastures of 10% could decrease deforestation in frontier regions of the Brazilian Amazon by up to 40%. Such mechanisms also point to the importance of the land tenure system and the land market for the deforestation process.

Policies to curtail deforestation are an important opposing force. Conservation areas have been created to protect large areas of the forest, but these measures are insufficient to reduce deforestation and need to be supplemented by conservation on private lands (Soares-Filho et al., 2006). These range from law enforcement and fines for illegal deforestation to limiting access to agricultural credit for activities in areas with high deforestation rates (Nepstad et al., 2014). A new implementation of the Forest Code, the current environmental legislation, includes the possibility to trade forest certificates (Soares-Filho et al., 2016). But also these measures have their limits for reaching zero deforestation soon (Azevedo et al., 2017). It is therefore an ongoing challenge to identify, assess, and implement policies to bring deforestation rates down.

In the course of this thesis, I will focus on some specific aspects of this complex system that I outline in the remainder of this introduction.

1.5. Outline of the thesis and main research questions

The thesis is structured as follows. Chapter 2 provides a theoretical basis for the modeling applications in this thesis. Human decision-making gives social and social-ecological systems unique properties that raise many question how they can be modeled. Therefore, I review modeling approaches to represent social and socio-economic systems and their interactions with ecological systems from a complex systems point of view. I introduce models of human decision making, review modeling approaches to social interaction, and discuss aggregation techniques and their relation to concepts from statistical physics. If available, I give examples for applications of

these approaches in land-use models. The main question driving the review in this chapter is:

Which theoretical approaches are appropriate to model human behavior in social-ecological systems?

This part of the thesis is based on an extensive review of modeling techniques, which have the potential to allow the representation of human behavior and decision making in Earth system models (Müller-Hansen et al., 2017b, P1). The review provides a systematic framework and basic introduction to social modeling approaches, mainly aiming at readers from the natural sciences. The chapter furthermore draws on my contribution to a discussion paper on the possibilities of modeling the socio-technical sphere of the Earth system (Donges et al., 2017a, P2).

Chapter 3 empirically analyzes land-use dynamics in the Brazilian Amazon. In order to capture the heterogeneities and patterns of the land-use changes in the region, I combine methods from Markov-chain analysis with clustering and network analyses. I present the patterns obtained with the method and discuss them in view of the literature. The main research question for this part is:

How can we identify patterns of land-cover transitions from highly resolved land-cover maps in dynamic regions such as the Amazon?

The last section of Chapter 3 discusses possibilities to use the obtained information in simple Markov-chain models to project future land-cover changes and shows the limitations of this type of models. The main results of this part of the thesis are published in Müller-Hansen et al. (2017a, P3).

Chapter 4 presents an agent-based social-ecological model that captures the dynamics of deforestation resulting from cattle ranching in a stylized way. The main goal of this model is to investigate the influence of processes and their interaction in a qualitative way, especially regarding the effect of intensification on deforestation. The model does not serve to provide quantitative scenarios or predictions of future deforestation rates. The main research question driving this modeling exercise is therefore:

Can intensification of cattle ranching in Amazon frontier regions reduce deforestation?

I present a detailed analysis of the model dynamics and dependencies on parameters and discuss implications for anti-deforestation policies. The material of this part of the thesis is the basis for a paper submitted to Ecological Economics (P4).

Finally, Chapter 5 summarizes and discusses the results, and highlights promising avenues for future research on land-use change in the Amazon and social-ecological modeling of deforestation dynamics.

Chapter 2.

Modeling social systems and human-nature interactions

2.1. Introduction

This chapter provides an overview over existing approaches to model human behavior and decision making in the interaction with environmental dynamics, specifically in the land system. The review discusses the question: Which theoretical approaches are appropriate to model human behavior in social-ecological systems? It highlights the strengths and limitations of different approaches and their underlying assumptions about human behavior. The chapter is both a detailed overview of available modeling approaches and a discussion of crucial choices that modelers face when building models of social systems. The chapter proceeds explaining methodological issues and providing criteria that help deciding which modeling approach fits best for a given purpose.

This part of the thesis is based on a review paper that I lead-authored (Müller-Hansen et al., 2017b, P1) and a commentary that I co-authored (Donges et al., 2017a, P2).

I define decision making as the cognitive process of deliberately choosing between alternative actions. This may involve analytic as well as intuitive modes of thinking. Actions are intentional and subjectively meaningful for the agent. Behavior, in contrast, is a broader concept that also includes unconscious and automatic activities, such as habits and reflexes. The outcome of a decision is therefore a certain type of behavior, which may be explained by a theory of decision making.

The challenge in modeling human-nature interactions lies in the potentially complex feedbacks between ecological and social dynamics, the latter being determined by human decision making and social interactions. Various social-science theories for example from environmental economics, sociology, and psychology provide explanations for human behavior and decision making in environmental and ecological contexts. In this chapter, I focus on mathematical and computational models of human decision making and behavior, i. e., only theories that have been formalized. I define the terms ‘modeling approach’ as a class of mathematical or computational structures that can be interpreted as a simplified representation of physical objects and actors or collections thereof, events and processes, causal relations or information flows.

Modeling approaches draw on theories of human behavior that make – often contested – assumptions about the structure of decision processes. Furthermore, modeling approaches can have different purposes: The objective of descriptive models is to explore empirical questions (e.g., which components and processes can explain the system’s dynamics), while normative approaches help answering ethical questions (e.g., which policy we should choose to reach a certain goal).

In the context of human-nature interactions, only those human decisions and behaviors are of interest that have considerable impact on the environment. Such decisions include for instance reproduction, consumption, and production of energy- and material-intensive products, the place of living, resource extraction, and land management. For outcomes that alter the natural environment at the system-level, the following categories of decisions are most important: First, large-scale environmental consequences can result from the behavior of a large number of individuals gradually influencing the environment. For example, the above mentioned individual decisions lead to aggregate population dynamics, growth of the economy, resource depletion, or migration. Therefore, it is important to also model interactions between agents and aggregate their behavior and interactions to a system level. Second, decisions of single individuals can also be amplified through their position in social organizations and institutions or through technology. This is for example the case for policy makers creating incentives or disincentives for environmentally friendly behavior or business leaders investing in the development of clean or polluting technologies.

This chapter builds on the following overviews on existing modeling approaches and theories that are applied in the context of environmental management and change. Verburg et al. (2016) assess existing modeling approaches and identify challenges for improving these models to better understand the dynamics of the Anthropocene. An (2012), Meyfroidt (2013), and Schlüter et al. (2017) focus on cognitive and behavioral theories in ecological contexts, providing an overview for developers of agent-based land-use and social-ecological models. Cooke et al. (2009) and Balint et al. (2017) review different micro- and macro-approaches with applications to agro-ecology and the economics of climate change, respectively. The present chapter complements the literature by systematizing the different modeling approaches into three categories: (1) individual agent behavior, (2) agent interactions, and (3) aggregation of individual behaviors and interactions. These categories arise from a complex systems perspective on social systems comprised of multiple agents which interact and whose joint behavior and interaction give rise to emergent aggregate phenomena. Figure 2.1 summarizes the modeling approaches corresponding to the three categories and their assumptions about human behavior. I argue that only the combination of model ingredients from the three different categories can describe the interaction of social and ecological systems in a comprehensive way. This thesis exemplifies the combination of approaches with the agent-based model presented in Chapter 4.

Furthermore, this chapter links the approaches, techniques, and theories from the three categories to applications in land-use modeling. For this, I draw on several reviews of land-use models in the literature (Baker, 1989; Briassoulis, 2000; Brown et al., 2004; Michetti, 2012; Groeneveld et al., 2017). In this chapter, I will only make


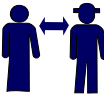

	Model category	Modeling approaches and techniques	Important considerations for model choice and assumptions
	Individual decision making and behavior	Optimal decisions in rational choice Heuristics/decision trees Learning theory	Motives, objectives, preferences Constraints, information and knowledge, beliefs, behavioral options and dispositions Decision rules, strategy selection
	Interactions between individual agents	Classical and evolutionary game theory Social influence models Networks of interaction structures	Strategic interaction, imitation of behavior, influence on beliefs, opinions, preferences, adaptation of interaction structure
	Aggregation and system-level description	Social welfare and voting Representative agent General equilibrium models Agent-based modeling Statistical distributions System-level models	Agent homo- or heterogeneity, positive or negative feedbacks, transient dynamics and equilibrium states, centralization of decision making

Figure 2.1.: Overview of modeling approaches and techniques discussed in this section and considerations for model choice and assumptions about human behavior and decision making.

reference to those type of land-use models that include decision making in one way or another, for instance economic optimization and agent-based models. Models of land-use change that are based on statistically estimated relationships are discussed in the subsequent chapter, Sect. 3.5.

The remainder of this chapter is structured in the following way: Section 2.2 discusses some general aspects regarding top-down versus bottom-up approaches to modeling social systems. It proceeds by specifying the three categories of modeling approaches introduced above and outlines the most prominent ones: First, Section 2.3 reviews approaches to model individual decisions and behavior from rational choice to learning theories. Second, Section 2.4 puts the focus on approaches for modeling interactions between agents and how to model interaction structures. Third, Section 2.5 reviews different aggregation techniques that allow describing human activities at the level of social collectives or systems. Finally, I briefly outline how computational agent-based approaches are used to model social-ecological systems (Sect. 2.6). Throughout the sections, I indicate how land-use and agricultural models make use of the different approaches. The discussion in Sect. 2.7 develops guiding principles that help modelers choosing appropriate modeling approaches. This thesis aims at fostering a better understanding between the social and natural sciences. Therefore, I highlight commonalities and differences between natural and social scientific models in the discussion. The chapter concludes with a summary of the lessons learned from this review.

2.2. Bottom-up and top-down approaches to modeling social systems

Decision making and behavior of humans can be described and analyzed at different levels of social systems. While the obvious level of analysis are individual humans, it is often more appropriate to model a social collective, such as a household, neighborhood, city, political or economic organization, or state as one decision maker. A modeling approach to represent a social system can put a stronger emphasis either on individuals or collectives. The choice of a suitable level of description and modeling approaches therefore strongly depends on the purpose of the modeling exercise.

The relation between individual agents and social collectives and structures has been the subject of considerable debate in the social sciences: The social-scientific tradition of methodological individualism⁴ aims to explain social macro-phenomena, e.g., phenomena at the level of groups, organizations, or societies, with theories of individual behavior. In contrast, structuralist traditions claim that collective phenomena are of their own kind and therefore cannot be traced back to the behavior of individuals (Durkheim, 2014). In sociology and social philosophy these opposing views are discussed as the problem of structure and agency (Elder-Vass, 2010; Ritzer, 2010). The philosophy of action defines agency as the capability of an agent to perform deliberate and intentional action, as opposed to forced not random behavior (Schlosser, 2015; Moya, 1990). Individuals whose actions are determined or even forced by the social structure cannot have agency. Therefore, agency refers to the autonomy of the individual from the structure. Many social theories emphasize the interdependency of individual agency and social structure, which is understood as an emerging phenomenon that stabilizes particular behaviors (Coleman, 1994; Ritzer, 2010). They acknowledge that agency is one side of a dialectic understanding of the social as an interdependent relation of individuals and social structure. I take a complex systems perspective acknowledging that emergent collective phenomena can be based on the interplay of individual behavior and that interactions of individuals give rise to structures that cannot be reduced to single individuals. Furthermore, interdependent individual actions can have unintended social outcomes.

Especially in contemporary mainstream economics, models are required to be based on microfoundations, i.e., models of individual behavior (Janssen, 2008). This has the following reason: The statistical correlations between aggregate variables may become invalid if the consequences of shifts in policy are anticipated by the agents in the social system, which may break these relationships. In economics, this is known as the Lucas critique (Lucas, 1976). The same argument applies to social-ecological systems. To inform policy makers about the potential consequences of policy intervention in a social-ecological system, models must allow insights into how the social system and the environment will respond to an intervention. To achieve

⁴There are different accounts of methodological individualism and it often remains unclear to what extent structural and interactionist elements can be part of an explanation (see Hodgson, 2007; Udehn, 2002).

2.2. Bottom-up and top-down approaches to modeling social systems

this, they need to be based on a firm representation of human behavior and decision making that capture their dynamic and adaptive characteristics. For such purposes, even the most accurate statistical description of human behavior is insufficient for the following reason: In a closed interaction loop with their natural environment, humans constantly respond to changes, facing novel conditions and problems, which makes it difficult for a statistical model to capture them. Theoretical accounts need to complement the statistical models. Otherwise policies can fail to achieve the desired results. This is true for intervention programs ranging from incentives schemes to social institutions and nudges (Ostrom, 1990; Thaler and Sunstein, 2009). Without a strong theoretical basis, a purely statistical model cannot guarantee that policies will lead to the intended changes in the system.

Selecting and developing such a theoretical basis further is a challenge that has led to many controversies in the social sciences. There is no single theory of human behavior that can be taken as a general law (Rosenberg, 2012). The understanding of human decision making and behavior is limited because its determinants are often contingent and socially formed by norms and institutions. Even if humans as part of the physical world are subject to natural laws, their decisions are not fully determined by them (otherwise we would not call it a choice). Decisions are influenced by thoughts, feelings, and complex world views, just to name a few determinants. This allows a view on social systems as socially constructed realities, which is in stark contrast to the positivist epistemology of one objective reality prevalent in the natural sciences. Past attempts to develop grand theories of human behavior have thus been criticized for being too remote from reality and, as a consequence, hard if not impossible to test empirically (Hedström and Udehn, 2009; Hedström and Ylikoski, 2010; Merton, 1957).

For this reason, many social scientists put forward a so-called “middle-range approach”: theoretical models are chosen for and adapted to specific contexts rather than trying to accommodate the various behaviors in different situations in one overarching, general theory. This approach supports that human behavior and decision making is very context dependent. For example, individuals act in some contexts egoistically and based on rational calculus, while in other contexts they may act altruistically and according to simple heuristics. The principles according to which the decision is made depend on, e. g., whether the decision maker has faced the decision problem before, the complexity of the decision, the amount of time and information available to the individual, and whether the decision affects others or is framed in a specific social situation. Likewise, the decision principles applied in a situation depend on the role that the actors have, their personality, and their social interactions.

With the requirement of microfoundations comes the problem of aggregating the behavior and decision making of individual agents to the level of the social system. This so-called aggregation problem poses huge mathematical challenges and leads to methodological problems when solved with simplification techniques like the representative agent approach. I will discuss such techniques as well as their limitations in Sect. 2.5.

The dichotomy between a micro- and macro-level suggests a separation, where there are various intermediate levels of social organization. This can result in treating very different phenomena alike. For instance, many economic models describe both small businesses and transnational corporations as actors on the micro-level and model their decision processes with the same set of assumptions, even though they often operate very differently. Therefore, it is crucial to choose appropriate levels of analysis, especially when modeling human-nature interactions in the context of global change. Depending on the research question, models need to bridge different levels ranging from individual to global institutions. Furthermore, they often need to integrate different spatial as well as temporal scales (Gibson, Ostrom, and Ahn, 2000). Table 2.1 provides an overview of important socioeconomic units (individual and collective agents) spanning these levels of social organization. It names scientific fields and communities that focus on the different agent types. The table also links them to theories, frameworks, and common assumptions on their decision making.

The issue of agency, its attribution, and perception is also related to the question at which level a description of the social system is appropriate. Even though the ability to act is usually ascribed to the individual, the perception of options and decisions between these options are often strongly shaped by social context and sometimes even required by institutions in the form of formal (e.g., law, property rights) or informal social rules (e.g., norms, religion). Formal rules often manifest themselves in social, political, and economic organizations and influence informal rules, thus strongly shaping the decision situation for individuals. Organizations can develop their own dynamics causing outcomes unintended by their members. On the other hand, social movements initiated by few individuals can lead to disruptive changes in social structures. Therefore, the attribution and perception of agency is not only interesting theoretically, but is relevant for a good choice of the level of model description. It should focus on the most important agents of change.

2.2. Bottom-up and top-down approaches to modeling social systems

Table 2.1.: Overview of possible levels of description and the associated socioeconomic units or (collective) agents, scientific fields and communities, and common approaches and assumptions about decisions and behavior. The list gives a broad overview but is far from being exhaustive.

Level	Socioeconomic units/agents	Fields/ Communities	Common approaches and theories	Common assumptions about decision making
Micro	Individual humans	Psychology, neuroscience, sociology, economics, anthropology	Rational choice, bounded rationality, heuristics, learning theory	[All assumptions presented in this column]
	Households, families, small businesses	Economics, anthropology	Rational choice, heuristics, social influence	Maximization of consumption, leisure, profits
Inter-mediate	Communities (villages, neighborhoods), cities	Sociology, anthropology, urban studies	Social influence, networks	Transmission and evolution of cultural traits and traditions
	Political parties, NGOs, lobby organizations, educational institutions	Political science, sociology	Strategic decision making, public/social choice, social influence and evolutionary interactions	Agents form coalitions and cooperate to achieve goals, influenced by beliefs and opinions of others
	Governments	Political science, operations research	Strategic decision making, cost-benefit and welfare analysis, multi-criteria decision making	Agents choose for the common good
	Nation states, societies	Economics, political science, sociology	welfare maximization, social choice	Majority vote
Global	Multinational firms, trade networks	Economics, management science	Rational choice	Maximization of profits or shareholder value
	Intergovernmental organizations	Political science (international relations)	Strategic decision making, cost-benefit analysis	Coalition formation

2.3. Modeling individual behavior and decision making

This section discusses different theories of individual decision making and behavior. Most models can be categorized by their assumptions regarding three determinants of decision making: goals, restrictions, and decision rules (Lindenberg, 2001). First, the models assume that individuals have motives, goals or preferences. Usually, the models suppose that agents rank outcomes of a decision in terms of their desirability and seek to realize outcomes with a higher ranking. Second, decision models account for restrictions and opportunities that help or constrain agents in pursuing their goals. For example, decision makers form more or less accurate beliefs about the costs (e.g., money or time) associated to the different options of a decision problem and how likely they are to occur, depending on the information available to them. Furthermore, their ability to access and process information needed for the decision might be limited.

Third, models specify decision rules that translate the agents' preferences and restrictions into a choice. These decision rules can differ very much in their complexity, their explicitness, and their determinacy. However, they can roughly be categorized into three types: First, there are decision rules that are forward looking. Individuals list the future consequences of options and choose the options they judge result in the best outcomes. Second, backwards looking approaches, such as classical reinforcement learning, assume that actors tend to choose those behaviors that gave them higher satisfaction in the past. Third, sideward-looking decision rules account for behavior that agents adopted from others (Kandori, Mailath, and Rob, 1993). The different decision rules imply various degrees of context-dependency and implicit assumptions about the agents' underlying cognitive capabilities.

In the remainder of this section, I illustrate the assumptions about motives, restrictions, and decision rules regarding the three decision theories that feature most prominently in the literature: rational choice theory, bounded rationality/heuristic decision making, and learning theory. Table 2.2 summarizes the approaches focusing on individual decision making and behavior.

2.3.1. Optimal decisions and utility theory in rational choice models

Rational choice theory (RCT) models the goals of agents as preferences. The preferences represent a hierarchy of goals that the agents try to pursue. The model usually assumes that the agents choose the action that brings about the most preferred outcome given some external constraints. RCT has become the standard model in many social sciences, especially in economics, in part due to its strong mathematical foundation.

The questions about the demarcation between RCT and other decision theories and the question which actions qualify as rational is disputed. Opp (1999) distinguishes between a narrow and a wide version of RCT. The narrow version (sometimes referred to as the model of *homo economicus*) refers to purely self-interested agents that have full control and knowledge of their possible actions, information about the probabilities

2.3. Modeling individual behavior and decision making

Table 2.2.: Summary table for modeling approaches to individual behavior and decision making.

Theories	Key considerations	Strengths	Limitations
Optimal decisions in rational choice: Individuals take the decision that maximizes expected utility given external constraints	What are agent's preferences and constraints? How is utility combined for different probabilities, times, and issues? Which information (and beliefs) do agents have?	Highly researched theory with strong theoretical foundation	Individuals assumed to have strong capabilities for information processing and perfect self-control
Bounded rationality and heuristic decision making: Individuals use heuristic decision rules to navigate complex environments effectively	Which constraints to gather, store, and process information do agents have? Which heuristics are used to gather and evaluate information? When do agents stop gathering more information and take a decision?	Simple decision processes that capture observed biases in decision making	Suitable decision rules highly context dependent
Learning: Agents explore possible actions through repeated learning from experience	How stable is the environment with which agents interact? What is the trade-off between exploitation of knowledge and exploration of new options?	Captures information and belief acquisition process	High degree of randomness in behavioral changes

of possible consequences, and unlimited capacities to compute the optimal decision upfront. In many decision situations, humans do not decide as predicted by this version (e.g., Tversky and Kahneman, 1974; Kahneman, Knetsch, and Thaler, 1986; Kahneman, Knetsch, and Thaler, 1990).

The wide version of RCT relaxes some of these assumptions and therefore can be conciliated with a range of behavioral experiments. It allows for all kinds of preferences. Authors from the field of economics like Rabin (2002) often distinguish between standard and non-standard assumptions regarding preferences, beliefs, and decision-making rules, where the standard assumptions mostly correspond to the above mentioned strong version of RCT. For example, non-standard preferences can regard the consequences for other agents (other-regarding preferences and altruism, e.g., Mueller, 2003; Fehr and Fischbacher, 2003) or aspects of the decision-making process itself (procedural preferences, e.g., Hansson, 1996; Fehr and Schmidt, 1999). Furthermore, the wide version includes not only external but also internal constraints into RCT. These non-standard constraints can be beliefs about external constraints, understood as subjective probabilities, which do not need to reflect the actual external constraints. One example for such a theory is the *beliefs, preferences and constraints* model (BPC model, Gintis, 2009). However, accounts of RCT that are subsumed under the wide version have been criticized for being tautological because they explain behavior in terms of unobservable preferences, which in turn are derived from empirical observations of the behavior (e.g., Vanberg, 1994, p.27).

The remainder of this subsection introduces the core elements of RTC regarding the formalization of preferences, which allow describing the decision problem. Binary preference relations fulfilling certain criteria can be combined into a utility function. Utility theory then describes how utility can be combined for uncertain outcomes, different times, or across different interrelated issues. The standard decision rule is then to arrive at the chosen decision by optimizing over all possible options. In the next section (2.3.2), I discuss non-standard decision rules deviating from the standard assumption that agents always choose the optimal option.

Preferences are typically modeled as preference relations $x P_i y$, denoting that individual i prefers x to y , where x and y represent the outcomes of the decision process. In general, preference relations describe the valuations of an agent irrespective of external normative judgments regarding their content. In a probabilistic setting, they can also represent probability distributions of outcomes. A crucial but debated assumption of rational choice models is that preferences are stable over time, or at least that small changes in preferences can be neglected on the relevant time scales. The restriction to stable preferences is important to prevent trivial explanations, because a theory that models a given change in behavior as a result of a change in preferences (which cannot be observed directly) is tautological. Nonetheless, empirical research shows that individuals' goals and therefore also their preferences can change even on relatively short time scales (Ackermann, Fleiß, and Murphy, 2016). Modeling endogenous preferences that are not arbitrary but a result of social interaction or long-term social evolution could provide a way out of this dilemma (Bowles, 1998).

Many versions of RCT, first of all the standard expected utility theory, assume

that the binary relation P_i has two properties: (1) completeness, which means that for every pair (x, y) , x is either preferred to y or vice versa (either xP_iy or yP_ix), and (2) transitivity, which implies that if x is preferred to y , and y to z , then x also needs to be preferred to z (if xP_iy and yP_iz then xP_iz). More general preference relations are possible but not very common (for examples, see Fishburn, 1968; Heitzig and Simmons, 2012). The above-mentioned properties allow representing the preference relation P_i by a utility function u_i with $u_i(x) > u_i(y)$ if and only if $x P_i y$, which is defined up to positive linear (affine) transformations (Neumann and Morgenstern, 1953). Utility functions map combinations of behavioral outcomes to an ordinal scale on which the more preferred outcomes of the binary relation have a higher score than less preferred ones.

RCT can also be used to model decision making under uncertainty. Uncertainty here refers to stochastic outcomes whose probabilities are nevertheless known to the decision maker.⁵ Expected utility theory makes use of utility theory to evaluate risky prospects, i. e., probabilistic outcomes of a decision. The action associated with the risky prospect brings about the outcome x with a probability $p(x)$. Then, the risky prospect p with the highest associated utility $u_i(p) = \sum_x p(x)u_i(x)$ is taken. The linear combination of possible outcomes weighted by their probability means that agents are assumed to evaluate risky prospects in a risk-neutral way, i. e., they only compare the expected value of utility for different options. This is the usual assumption of the narrow version of RCT.

But decision experiments show that only a small percentage of people decide according to expected utility theory (Kahneman and Tversky, 1979). Most participants are risk-averse to losses and risk-seeking with respect to high gains, evaluating small probabilities much higher than expected utility theory suggests. This type of decision making can be described by prospect theory, a broader version of RCT, using appropriate non-linear functions v and w to weigh the probabilities and outcomes, such that the chosen risky prospect p maximizes the utility $u_i(p) = \sum_x w(p(x))v(u_i(x))$ (Kahneman and Tversky, 1979).

If a decision involves outcomes at different points in time, time preferences of the decision maker might also play a role for the chosen action. Time preferences are modeled by discounting the utility of future outcomes. It is assumed that the action is chosen that brings about the maximal inter-temporal utility $u_i(x) = \sum_t g(t)u_i(x, t)$, where $g(t)$ is the discount factor. Discounting with exponentially decaying factors $g(t) = e^{-\delta t}$ is often used in models because it is mathematically convenient and ensures that the decision is time-consistent, i. e., it makes no difference at which point in time the decision was taken. This is the standard assumption of the narrow version of RCT. There is nonetheless empirical evidence from decision experiments

⁵Some authors make the distinction between risk as probabilistic events with known probabilities (“known unknowns”) as opposed to (fundamental) uncertainty as such events without any knowledge about their probabilities (“unknown unknowns”, cp. Knight, 2006). Even though fundamental uncertainty is important in human decision making, the theories described here focus on events, for which the probabilities are known. One reason for this is that fundamental uncertainty is difficult to represent in models.

that people often discount in a time-inconsistent way (Ainslie and Haslam, 1992; Jamison and Jamison, 2011). For example, some people prefer getting one dollar today over two dollars tomorrow, but when asked today, they prefer getting two dollars in 8 days over one dollar in a week. Therefore, broader versions of RCT use hyperbolic weights $g(t) = 1/(1 + \delta t)^s$ for discounting, which capture that people's valuation in the short-term declines much faster than in the long-term.

If decisions and their outcomes are not related, the utility for evaluating a joint decision can simply be added. In the case that decisions are coupled or bring about consequences that have to be balanced and that can partially substitute each other, it might be necessary to aggregate preferences by a joint utility function. For example, take an agent deriving utility from time spent fishing $u_F(T_F)$ and reading books $u_B(T_B)$. There is only limited time available for the two activities $T = T_F + T_B$. Therefore, the decisions about how much time to spend fishing and reading are interrelated. Furthermore, the utility derived from fishing or reading an additional hour decreases with the time spent on the respective activity. Such a partial substitutability can be modeled by different utility functions, for example a Cobb-Douglas utility function $u = u_F(T_F)^\alpha u_B(T_B)^{1-\alpha}$ or a constant elasticity of substitution (CES) utility function $u = (u_F(T_F)^r + u_B(T_B)^r)^{1/r}$. These functions are also used to model the substitutability of goods in consumer theory (Varian, 2010).

It is possible to combine several of the discussed options that account for contributions to overall utility across different probabilities of outcomes, points in time, or issues. To model the decision process, the resulting utility function is taken as the objective function of a maximization problem with different types of constraints. The optimization problem can be solved computationally by mathematical programming techniques or analytically with calculus of variations (see e.g., Kamien and Schwartz, 2012; Chong and Zak, 2013). The solution (or one of the solutions) of the maximization problem is then taken as the chosen option of the decision problem.

In the context of agricultural economics, farm models are often built on utility or profit maximization approaches. Singh, Squire, and Strauss (1986) introduce a simple farm model, characterized by the decision problem how to allocate the available time to labor L and leisure X_l and how much of the produced agricultural staple Y to consume or sell on the market in exchange for other goods. The household utility $U(X_a, X_m, X_l)$ depends on the quantity of the consumed produce X_a , purchased other goods X_m , and leisure X_l . The utility is optimized subject to the following income constraint:

$$p_m X_m = p_a(Y - X_a) - w(L - F), \quad (2.1)$$

which depends on the price of the agricultural good p_a , the price of purchased goods p_m , the produced quantity of the good Y , the wage from external work w , available labor L and labor done on the own farm F . The produced agricultural good Y is a function of F and other inputs. The elasticities between different variables in the model are estimated from empirical data and used to give policy recommendations. Many farm models in agricultural economics are similarly based on utility or profit

2.3. Modeling individual behavior and decision making

maximization by farmers. They are also applied in agent-based models of land use (e. g., Andersen et al., 2017).

Decision making under risk in the land-use context has been studied with rational choice models for example by Quaas et al. (2007). They present a model of grazing management of cattle ranchers. In the model, biomass growth and therefore cattle production depends on stochastically varying precipitation, resulting in variable income for ranchers. The authors use myopic optimization and expected utility theory to derive a strategy that determines the fallow fraction of the pasture so that biomass can regenerate as an insurance to little precipitation.

From the comparison of RCT with the following decision theories, I conclude that rational choice approaches are appropriate for describing decisions of agents with sufficiently clear goals, who can easily access information, and have the time and cognitive resources to recognize and assess all available options. Such decisions may include for example individuals' decisions regarding long-term investments or strategic decisions of organizations such as firms or governments in competitive situations. Rational choice can also be a useful assumption when actors make the same decision many times and get immediate feedback, so that they learn the optimal decision fast. In this case, they behave "as if" they were rational decision makers. Besides being a descriptive model for optimal decision making, RCT also serves as a normative benchmark to compare with non-optimal approaches. Such approaches are discussed in the following section.

2.3.2. Bounded rationality and heuristic decision making

Empirical research, for instance in lab experiments, has shown that human decisions are not independent from the framing and context of a decision problem (Tversky and Kahneman, 1974). They are instead characterized by systematic deviations from the predictions by rational choice models. Such deviations are called cognitive biases. Cognitive biases have been explained by having limited time to process information (Hilbert, 2012), the existence of heuristic decision rules (Simon, 1956), and emotional influences on the choice (Loewenstein and Lerner, 2003), for example wishful thinking (Babad and Katz, 1991). Bounded rationality theory describes agents as being only partially rational. Their decision process is constrained by their cognitive capabilities to access, store, and process information (Simon, 1956; Simon, 1997). In the economic literature, some authors also consider non-standard preferences with time-inconsistent discounting, loss aversion, or risk-seeking as part of boundedly rational behavior. It therefore depends on the account of RCT whether a behavior that can be described by such preferences is judged to be rational in the sense of the wide version of RCT (Gintis, 2009).

An important aspect of bounded rationality is that agents are often not supposed to collect all information to evaluate the utility of every possible option of a decision problem and choose the optimal option afterwards. Instead, they evaluate only a limited number of options using for example heuristic decision rules for obtaining, processing, and judging the available information and for choosing actions. Such

decision rules are classified as non-standard in the economic literature (Rabin, 2002). An important type of strategy used to describe such decision processes is satisficing behavior: agents evaluate possible actions considering the available information and using their cognitive capabilities until an option is found that satisfies certain (possibly adaptive) criteria (Simon, 1956).

Regarding heuristic decision rules, Gigerenzer and Selten (2002) put forward a prominent account of what they call “fast and frugal heuristics”. They define heuristics as decision strategies that do not consider all information such that agents can make decisions faster and more frugally. According to this framework, decision makers are equipped with an “adaptive toolbox” containing a variety of heuristic rules adequate for specific contexts and environments (Gigerenzer and Gaissmaier, 2011; Todd and Gigerenzer, 2007).⁶

Such heuristic rules can be formalized for example in decision trees or flowcharts, combining three ingredients: (i) information search, i.e., the active search for information relevant for the decision at hand, (ii) criteria for stopping information search, and (iii) rules for deriving a decision from the obtained information. Pieces of information, so-called cues, are used to decide whether to continue the information search and choose between possible options or classify an object.

The take-the-best heuristic illustrates these ideas best. This heuristic is formalized as a cue order, i.e., the order in which different pieces of information are processed. Starting from the beginning of the cue order, the decision process proceeds step-wise. For each item in the cue order, relevant information is searched and evaluated. If the found information does not allow a discrimination between the available options, the process goes on to the next cue. This is repeated until a cue is reached, for which the available information makes a discrimination between options possible and the option with the higher cue value is chosen. Other examples for heuristics discussed within this framework can be found in Gigerenzer and Gaissmaier (2011).

Heuristic rules formalized in cue orders or decision trees are not only mere practical methods to structure the decision process and to help making a satisfying decision. They also encode norms and preferences of the decision maker because they give a higher priority to certain features of an option or outcome over others.

Heuristics have been used for analyzing decision making in various contexts, from the behavior of voters (Lau and Redlawsk, 2006) to behavior in organizations (Loock and Hinnen, 2015; Simon, 1997). However, they are not yet widely applied in dynamic modeling of social-ecological systems. A notable example of the application of fast

⁶Gigerenzer and Todd (1999) do not only challenge the empirical validity of RCT. They also question the role of RCT as the standard normative benchmark. They argue that RCT is inappropriate to account for the properties of what they call ‘large worlds’, which are decision environments characterized by important information being frequently unknown or coming from small and divergent samples. Heuristic decision making often results in equally good or even better decisions than more elaborate decision strategies in such environments (Dhimi and Ayton, 2001; Keller, Czienskowski, and Feufel, 2014). Gigerenzer and Todd therefore conclude that heuristics are not the product of cognitive constraints and biases but can be regarded as “ecologically rational”, in the sense that heuristics can serve as a normative choice model providing context-specific rules for normative questions.

and frugal heuristics is a model of farmer and pastoralist behavior in a conflict in east Africa (Kennedy and Bassett, 2011). Another example is the application of decision trees to simulate decision making in an agent-based model of land-use change in the Amazon (Deadman et al., 2004). Each household in the model is a potential farmer who first decides based on a subsistence requirement whether to farm annual crops or engage in another agricultural activity. The choice between different activities depends on factors such as the soil quality, which are sequentially evaluated. In the model, the heuristic decision tree simplifies a complex decision processes in a tractable and intelligible way. On the one hand, this shows the possibilities of this methods, while on the other hand revealing the abstraction from a real decision process and the many degrees of freedom in the construction of such heuristic rules from empirical evidence.

Heuristics can capture decision making in a computationally efficient way. Therefore, they can be used for example to represent the long-term evolution of decision rules or norms and values encoded in cue orders in computational social-ecological models. Recent studies investigate the spreading of cue orders via social interactions (Gigerenzer, Hoffrage, and Goldstein, 2008; Hertwig and Herzog, 2009). Such processes can be the basis for modeling norm and opinion spreading in social influence and network model (see Sections 2.4.3 and 2.4.4). Accounts like bounded rationality and heuristic decision making provide formalizations to capture human behavior that is not always consistent or optimal in the sense of RCT. However, they do not specify the adaptivity of these decision rules. For this, meta rules for learning and adapting the behavior according to the success of a behavioral strategy are needed. This is the focus of the following section.

2.3.3. Learning theory

The approaches discussed in the previous two subsections take the perspective of a forward-looking agent. Rational or boundedly rational actors optimize future payoffs based on information or beliefs about how their behavior affects future payoffs, while the procedures to determine options with higher payoffs are constrained. These techniques do not specify how the information is acquired and how the beliefs are formed. Computational learning theory focuses on behavior from a backward-looking perspective: an agent learned in the past that a certain action gives a reward, feels good, or is satisfying, and is therefore more likely to repeat this action. The theory can describe the adaptivity of agent behavior to a changing environment and is particularly suited for modeling repeated behavior under limited information. To model the learning of agents unsupervised learning techniques are used because they do not require training with external correction.

Reinforcement learning is a technique that models how an agent maps environmental conditions to desirable actions in a way that optimizes a stream of rewards (and/or punishments). The obtained reward depends on the state of the environment and the chosen action, but may also be influenced by chosen actions and environmental conditions in the past. According to Macy, Flache, and Benard (2013), reinforcement

learning differs from forward-looking behavioral models regarding three key aspects. (1) Reinforcement learning does not need to assume that the consequences of an action are intended because agents explore the likely consequences and learn from outcomes that occurred. In contrast, RCT assumes that agents choose an option with the intention that an outcome occurs, which must not happen in situations with probabilistic outcomes. (2) Decisions are guided by rewards or punishments, which lead to approach or avoidance, rather than by static utilities. (3) Learning is characterized by stepwise amelioration. Learning approaches model the dynamic search for an optimum and do not assume that the optimal strategy can be determined immediately.

The learning process is modeled via a learning algorithm (e. g., Q-Learning, SARSA-Learning, Actor-Critic-Learning), based on iteratively evaluating the current value of the environmental state utilizing a temporal difference error of expected value and experience value (Sutton and Barto, 1998). Artificial neural network algorithms can explore very high dimensional state and action spaces. Genetic algorithms, which are inspired by evolutionary mechanisms such as mutation and selection, are also used in learning problems. The learning algorithm balances a trade-off between the exploration of actions with unknown consequences and the exploitation of current knowledge. To not only exploit the currently adopted strategy, many algorithms use randomness to induce deviations from already learned behavior.

The environment in reinforcement learning problems is often modeled with Markovian transition probabilities. The special case of a single agent is called Markov decision process (Bellman, 1957). In each of the discrete states of the environment the agent can choose from a set of possible actions. The choice then influences the transition probabilities to the next state and the reward. One caveat of these learning approaches is that they can fail, if the environment changes faster than agents can explore their options and adapt their behavior accordingly. Therefore, the environment and the probabilities for the payoffs are usually assumed to be stable.

A common approach to model the acquisition of subjective probabilities associated with the consequences of actions is Bayesian learning, which has also been applied to reinforcement learning problems (Vlassis et al., 2012). Starting with some prior probability (e. g., from some high-entropy “uninformative” distribution) $P(h_i)$ that some hypothesis h_i about the relation of actions and outcomes is true, new information or evidence $P(E)$ is used to update the subjective probability with the posterior $P(E|h_i)$ calculated with Bayes’ theorem: $P(h_i|E) = P(E|h_i)P(h_i)/P(E)$ (Puga, Krzywinski, and Altman, 2015). The most probable hypothesis can then be chosen to determine further action.

The combination of various approaches to model the acquisition of beliefs through learning, the formation of preferences, and different decision rules discussed in the previous sections with further insights from psychology and neuroscience has led to the development of very diverse and detailed behavioral theories. Some of them have been formalized in so-called cognitive architectures (Balke and Gilbert, 2014). These approaches can be used to describe human behavior in computational models, but are too complex and diverse to discuss them in greater detail.

Besides the forward- and the backward-looking approaches to behavior introduced in this section, agents may exhibit sideways-looking behavior: agents can copy the behavior of successful others, thereby contributing to a social learning process. For this kind of behavior, interactions between different agents are crucial. This will be the focus of the next section.

2.4. Modeling interactions between agents

In the previous section, I discussed modeling approaches focusing on the choices of individual agents that are confronted with taking a decision in a specified situation. This section reviews techniques to model structured or local interactions of agents. This includes how agents influence each other and how they anticipate and respond to each other's decisions. In general, it is not only individuals who interact in bi- or multilateral ways but also collective agents or groups at various levels. This section focuses on interactions for which the interaction structure is relevant. Interactions at the system level that also serve as aggregation mechanisms (e. g., voting procedures and markets) will be discussed in Sect. 2.5.

This section starts with an introduction to strategic interactions as modeled in classical game theory and dynamic interactions of strategies in evolutionary approaches. Then, I discuss models of social influence that are used to study opinion and preference formation and the transmission of cultural traits, i. e., culturally significant behaviors. Finally, I highlight the use of graph theory and dynamic network models to represent social interaction structures. This subsection also shows the relations between network models studied in sociology and statistical physics, illustrating the contributions that physics approaches can make to the understanding of social systems. Table 2.3 summarizes the different modeling approaches that focus on agent interactions.

2.4.1. Strategic interactions between rational agents: classical game theory

Game theory describes decision problems in which the outcomes depend on the choices of two or more decision makers. The utility gained from the outcome, which is usually called payoff in game theory even if it must not refer to some payment, depends on the choice of actions of several decision makers, called players. Such interdependent decision problems are often situations of conflict or cooperation.

Games are formally described by so-called game forms (also called game mechanisms). For every step in the game agents choose an action or move $a_i(t)$ from an action set $A_i(t)$. Actions may include communication with the other players (called signaling) or committing to binding agreements (commitment power). If a game involves only few combinations of actions, it can be formalized as a payoff matrix. Alternatively, a game tree is used to describe it. Game trees are directed graphs (see Sect. 2.4.4). Their nodes represent the status of the game and the outgoing edges are different possibilities for actions (Gintis, 2009).

Table 2.3.: Summary table for modeling approaches to agent interactions.

Approaches and frameworks	Key considerations	Strengths	Limitations
Classical game theory: strategic interactions between rational agents	How is the game structured in terms of possible actions, payoffs, communication, and information flow? How can recursive relations of agent beliefs and strategies be solved?	Self-consistent solutions for low-complexity problems	Difficult to solve for complex games, agents cannot change the rules of the game
Evolutionary game theory: variation, selection, and reproduction of acquired or adapting strategies	How do strategies perform against each other? Can agents adapt or imitate strategies? How do reproduction mechanisms interplay with the payoff structure of games?	Explains how dominant strategies come about	Strategies of agents are usually fixed, not accounting for conscious strategy changes
Social influence: agents influence each other's beliefs, opinions, or behaviors	How do influence mechanisms change the attributes of agents? Is the influence positive or negative, bilateral or multilateral? How are random deviations distributed?	Allows to model social learning, opinion formation, and herding behavior	Local dynamics are often stylized
Network theory: changing social interaction structures	How much randomness and hierarchy is in the structure? Is the social network static or adaptive? How do agents form new links?	Mathematical formalization to model the co-evolution of social structure with dynamical attributes of agents	Local interactions and updating rules often dyadic and schematic

There are different approaches to investigate such games and different strategies to play them. Strategies are rules defining how the action for every step of the game (or node in the game tree) is chosen, possibly including deliberate randomization of choices. In contrast to the chosen actions, strategies are not observable. Because many nodes of a game tree may not be reached in the realization of the game, it is generally not possible to deduce the underlying strategy from the actions of an agent. Different approaches to game theory investigate how strategies interact and how they bring about different outcomes for the players. Classical game theory focuses on how rational decision makers choose strategies. Evolutionary approaches explore which strategies prevail or dominate other strategies in a population of players with different strategies if the reproduction of a strategy depends on its relative success. In the remainder of this section, I will discuss some basic ideas of classical game theory. The next section introduces evolutionary approaches.

Classical game theory assumes that players choose their strategies according to rational choice theory and that they take the rationality of other players into consideration when determining their strategy. Assuming the rationality of other players implies that their behavior also results from the optimal strategy for them. Therefore, the rationality of players has to be common knowledge such that the strategies of all players are consistent with their beliefs about the strategies of the others (Sugden, 1991).

The belief that the other players follow a rational strategy often leads to recursive relationships between beliefs and strategies, making solutions of games complex and difficult to find. The solutions are called equilibria even though this does not refer to dynamic equilibria but to fixed points of the recursive problem. A very important solution concept in game theory is the so-called Nash equilibrium. It describes a situation in which players assume that their counterparts choose an equilibrium strategy and cannot gain more by changing their own strategy. Nash equilibria can be found using elaborate non-linear fixed-point solvers (Harsanyi and Selten, 1988). Some simple games can also be solved by a method called backwards induction (Gintis, 2009). However, complex games often have multiple Nash equilibria and the concept leaves open which one is preferable. Therefore, further criteria have been developed to account, for example, for consistency of strategies over time or in subgames, or for resistance against small mistakes (Harsanyi and Selten, 1988). Once the solution methods have identified equilibrium strategies, these strategies can be used to model the agents' behavior, for example in simulations of many interacting agents.

In general, game theoretic models can break down complex decision situations to stylized decision problems. A paradigmatic example for this is the prisoner's dilemma, in which two players can choose to either cooperate or defect. In the prisoner's dilemma, the strategy corresponding to the Nash equilibrium produces the worst outcome for the players. For such simple games, classical game theory suggests that agents do not or only rarely cooperate. As models become more complex and include options to signal, share information, punish or form coalitions, equilibrium strategies involve higher levels of cooperation (Kurths, Heitzig, and Marwan, 2015).

Classical game theory is primarily applied to model strategic interactions in market

settings (see also Section 2.5.2), but also to model international relations of states or political decisions such as voting behavior (public and social choice theory, e. g., Ordeshook, 1986; Mueller, 2003, and Section 2.5.4). Complex games can involve different types of actors. International negotiations and their interactions with domestic policy have been modeled for example by so-called two- or multilevel games (e. g., Putnam, 1988; Lisowski, 2002). Regarding the application to social-ecological systems, game theory has been used to describe dilemmas in the usage of common pool resources (e. g., the commonize costs - privatize profits game, see Hardin, 1985) and international climate policy (e. g., variants of the public goods game, see, e. g., Heitzig, Lessmann, and Zou, 2011).

Classical game theory is appropriate for describing strategic interactions between highly rational and well-informed agents. This may apply for example to international negotiations between governments⁷, bargaining between social partners, or monopolistic competition between firms. However, if the situations of interdependent decisions are very complex, it may be difficult for agents to see through the whole game structure and evaluate the huge number of possible strategies. In such situations, evolutionary approaches can help to evaluate different strategies, as the next section illustrates.

2.4.2. Interactions with dynamic strategies: evolutionary approaches and learning in game theory

Evolutionary approaches to game theory analyze which strategies score higher payoffs when playing against each other in a formal game and explore the dynamics of the prevalence of strategies over time. For this, they combine three mechanisms: variation, selection, and reproduction of strategies. In biological evolution, this can be linked to genetic mutation, selection by fitness, and reproduction with inheritance. However, the application of these principles has a far wider scope, ranging from cultural evolution (Axelrod, 1997) to social learning (Macy and Willer, 2002).

In general, the individual strategies in evolutionary games can be hard-wired, acquired (e. g., through imitation), or adapted via learning rules (Fudenberg and Levine, 1998; Macy and Flache, 2002). Variation of strategies can be modeled by randomization or active adaptation of agents' strategies. The number of possible strategies can be reduced by assuming that agents behave myopically (not accounting for payoffs far in the future) or decide based on heuristic rules or short memory (basically different kinds of boundedly rational agents, see Sect. 2.3.2). Payoffs in evolutionary game theory are usually related to the fitness of an agent (following the terminology of evolutionary biology) and determine the reproduction of its strategy. Thus, the game can be interpreted as a selection mechanism.

Regarding the reproduction of strategies, the number of agents and their relative shares change according to some replicator rule, which depends on their fitness or

⁷Even though game theory was formalized earlier, the field of game theory experienced a boost during the Cold War because it helped modeling the strategic interactions of the opposing states (Hagemann, Kufenko, and Raskov, 2016).

payoff. Changes in the shares of agents that follow a specific strategy can also be the result of an imitation process, in which more successful strategies are imitated at a higher rate.

A simple example for modeling the selection of strategies is the replicator equation that describes the results of interactions in a well-mixed large population. It describes the relative change in a subpopulation ρ_i with strategy i , which is proportional to the deviation of the fitness of this subpopulation from the average fitness (Nowak, 2006). For a game given by the payoff matrix \mathbf{A} , the standard variant of the replicator equation reads

$$\dot{\rho}_i / \rho_i = (\mathbf{A}\rho)_i - \rho^T \mathbf{A}\rho. \quad (2.2)$$

This selection mechanism lets strategies that achieve higher payoffs prevail on a population level. Dominant strategies can be identified by studying the equilibria of the resulting dynamic system. The central concept of evolutionary game theory is evolutionary stability. An evolutionary stable strategy has the property that it cannot be invaded by other, initially rare strategies. This concept is refined for finite populations with noisy dynamics (stochastically stable equilibria, Foster and Young, 1990).

For more complex replicator or imitation dynamics, agent-based computer simulations can model local interactions to determine equilibrium strategies. However, this type of model needs finite or low-dimensional action sets and has to restrict the possible strategies to certain simple types (cp. also Sect. 2.6). Furthermore, the local interaction structure in such models, often represented by a network (see Sect. 2.4.4), can have a huge impact on the outcome (Szabó and Fáth, 2007; Perc and Szolnoki, 2010). A well-studied example is the iterated version of the prisoners' dilemma. Strategies in such a game include replicating the previous action of the other player (to retaliate defections) or forgiving defections with a small probability by not retaliating them. The model has been used to explain the emergence of cooperation in populations of primarily self-interested individuals (Axelrod, 1984).

Evolutionary approaches are rarely used in land-use models. A notable exception is the application of evolutionary programming techniques in an agent-based model of deforestation and reforestation, capturing the evolution of agents' internal strategy functions (Manson and Evans, 2007).

Evolutionary approaches to game theory can help to better understand the prevalence of certain human behavior regarding the interaction with the natural environment. This is especially interesting for modeling the long-term cultural evolution and changes in individuals' goals, beliefs, and decision strategies or the transmission of endogenous preferences (Bowles, 1998).

2.4.3. Modeling social influence

Human behavior is strongly influenced by social interactions. Such influences can be based on information exchange, perceived social pressure, or identification. For

example, agents are persuaded by other's ideas, arguments, or opinions (Myers, 1982; Wood, 2000; Feldman, 2011). Influence can result from identification with a group or highly regarded others (Akers et al., 1979), for instance an idol, or the desire to differentiate from other groups. In groups, individuals exert pressure on each other to conform with an attitude or opinion held by the group (Festinger, Schachter, and Back, 1950; Homans, 1950). Furthermore, the imitation of the behavior of peers can be a strategy to deal with the uncertainty of what is an appropriate behavior in a given situation (Bikhchandani, Hirshleifer, and Welch, 1992). Models of social influence study the effect of such influences between individuals and try to explain their system-level outcomes, for instance the formation of consensus or polarization of opinions and the spread of information, fashions, and norms.

In the following, I discuss different possibilities to formalize processes of social influence and their underlying assumptions. These assumptions concern the modeling of the effect, dimensionality, and direction of social influence as well as the question whether the influence is dyadic or multilateral. In the latter case, the question arises how the joint effect of multiple interactions is modeled. Finally, stochastic influences can model individual deviations and have an effect on the diversity of agents' attributes in models of social influence.

The effect of the influence on the attributes of an agent like opinions, norms, or attitudes is often positive such that agent's attributes become more similar (Friedkin, 1998). In the simplest case, an agent copies the attribute(s) of an interaction partner. Models of such processes with discrete attributes have been studied extensively in the mathematics and physics literature and are known as contact processes or voter models (Liggett, 1999). The influence can also be modeled by updating the agent's attribute(s) with the average over the attributes of all participants in the interaction. The overall effect of positive influence may not necessarily lead to consensus but can also lead to polarization, for example in models of argument communication (Mäs and Flache, 2013). Social influence can also have a negative effect resulting in divergent attributes of agents, even though the empirical evidence for such processes is mixed (Takács, Flache, and Mäs, 2016).

Models also assume different dimensionality of influence and attributes of agents. Attributes like political opinions can for example be binary, discrete, continuous, or even multi-dimensional. Political options are often modeled as binary choices, while continuous scales are used to describe quantitative difference, for instance in opinion polarization (Martins, 2008; Hegselmann and Krause, 2002). Models with multi-dimensional opinion spaces do usually not show opinion polarization and clustering (Axelrod, 1997).

The direction of influence plays an important role for model outcomes. In models of opinion dynamics, the influence is usually bi-directional: interacting agents can influence each other mutually (Hegselmann and Krause, 2002). In diffusion models, in contrast, the effective influence is directed. For instance, information can spread only from informed to uninformed individuals, not the other way around (Shakarian et al., 2015). Furthermore, the interaction structure modeled by a directed network can

impose directionality (see Sect. 2.4.4), e. g., representing unidirectional information flow in hierarchical organizations.

The influence between agents can be modeled as a bilateral or multilateral process. One possibility is to model the influence of a group on an actor as a sequence of bilateral interactions. In each interaction, the agent copies or adapts her or his attributes based on the influence of the interaction partner. For some types of interaction (e. g., interaction in small groups) it is more plausible to model the influence as a multilateral process. Then, the attributes of an agent are updated considering all influences exerted by multiple interaction partners at once (Huckfeldt, Johnson, and Sprague, 2004). To account for the various influences, models assume different forms of averaging: Some models use simply the arithmetic mean, which averages out extreme views in the interaction (Lorenz, 2005; Nowak, Szamrej, and Latané, 1990). Using instead the mode of the attributes of the influencing agents can imply that agents with rare traits do not make a difference in the interaction (Flache and Macy, 2011).

Finally, deviations in social influence processes can be modeled by noise terms for example in averaging or imitation. Here, the distribution of stochastic variables can have a considerable effect on model outcomes (Kurahashi-Nakamura, Mäs, and Lorenz, 2016). In bounded confidence models, individuals only interact if the difference of their opinions on a continuous scale lies within a given threshold. Including normally distributed noise into such models results in the fluctuation of the opinions of homogeneous subgroups. Over time, this will make subgroups with similar opinions merge that otherwise were too far apart to interact (Mäs, Flache, and Helbing, 2010). On the other hand, the introduction of uniformly distributed deviations can lead to an ordered state with distinct stable subgroups (opinion cluster), not emerging in settings with Gaussian deviations (Pineda, Toral, and Hernández-García, 2009). This can be explained by the fact that Gaussian noise needs to be very strong to generate enough diversity for the emergence of subgroups with different opinions. However, when noise is strong, subgroups will not be stable.

In land-use models, approaches to represent social influence are not yet widely applied. There are some agent-based approaches, that use social influence to simulate the effect of technology diffusion (Berger, 2001) or explore the impact of imitating behavior (Polhill, Gotts, and Law, 2001). But there remain many possibilities to explore the presented techniques in the context of land-use change further. For instance, they can be used to model under which conditions social learning enables groups of agents to take hold of sustainable management practices. The agent-based model developed in this thesis (see Chapter 4) makes use of social learning theories to describe the adoption of land management practices and techniques in the process of land-use intensification.

The effects of social influence depend on the structure of the network that determines who influences whom. Complex dynamics can arise when this interaction network is dynamic and depends on the attributes of the agents, as we discuss in the following section.

2.4.4. Network models of social structure

In most of the models discussed in the previous section, the agents interact on a social network, which determines the structure of possible interactions. This structure is usually non-trivial, i. e., it does neither allow all agents to interact nor is it homogeneous, as for instance a regular grid. This section gives an introduction to the formalization of interaction structures in graph theory, allowing to characterize the structure by statistical indicators. I discuss typical properties of social networks and indicate their application in models of social influence. Finally, I review adaptive network models, in which the network structure is affected by the interaction processes on the network, and applications of networks in social-ecological modeling.

Graphs are mathematical objects. In the physics literature, these objects are often simply called networks. In the following, I will use the terms interchangeably. A graph G is a pair $G = (V, E)$ consisting of a set of nodes or vertices $V = \{v_i\}$ and a set of links or edges $E = \{e_{ij}\}$, which connect some nodes of the graph (Newman, 2010). The edges $e_{ij} \in E$ are pairs of elements in V , $e_{ij} = (v_i, v_j)$. Graphs can be undirected or directed. For undirected graphs $e_{ij} = e_{ji}$, i. e., the order of pairs does not matter. Edges of directed graphs are ordered pairs. The edges may also be weighted with weights w_{ij} representing the strength of connections. Two nodes of a graph are called adjacent or neighboring, if they are connected by an edge. A graph can be represented by its adjacency matrix \mathbf{A} , defined by the following entries:

$$A_{ij} = \begin{cases} 1 & \text{if } e_{ij} \in E \\ 0 & \text{else.} \end{cases} \quad (2.3)$$

The adjacency matrix of undirected networks is symmetric, while that of directed ones is not. There are a variety of classes of graphs ranging from regular graphs (also called lattices), trees, and complete graphs (where all the vertices are connected) to random graphs. Complex networks have a structure (also called topology by network scientists) that is neither entirely regular nor entirely random. Instead, they have many properties also found in real-world networks like infrastructural, biological, and social networks.

The properties and structure of graphs can be compared based on several statistical tools. Indicators that are based on the node's position in relation to other nodes in the network are called centrality indicators. The most important representative of a centrality indicator is the degree of a node v_i , which is simply the number of its adjacent nodes $k_i = \sum_j A_{ij}$. There exist a variety of other indicators like eigenvalue, closeness, and betweenness centrality, which are related to random walks on the graph, the average distance to other nodes, and the ratio of shortest paths passing the node. A graph can be characterized by the distributions of its centrality indicators or their mean and higher-order statistical moments. Furthermore, one can characterize the correlations of these indicators between adjacent nodes (assortativity). Finally, there are global indicators measuring some property of the graph like for example the clustering coefficient (the normalized number of triangles), the average path length

(mean of shortest paths between all pairs of nodes) or the diameter (the longest shortest path in the graph).

This mathematical framework can describe social networks, in which nodes represent agents and links indicate interaction, communication, and social relationship. Agents can only directly interact and thus influence each other if they are connected by a link in the network. Thus, network models can be regarded as a type or component of agent-based models (Snijders, Bunt, and Steglich, 2010; Snijders and Steglich, 2015, see also Sect. 2.6).

Large social networks can be characterized by properties that are common to other real-world networks. For example, they have the small world property, meaning that even though agents are not connected to many others, they can on average reach every other agent in the network by a short chain of intermediaries. In terms of network indicators, such a property is associated to a small average shortest path length and a high clustering coefficient. Furthermore, some social networks are scale-free, having a degree distribution that can be approximated by a power law. In physics and mathematics, network models have been designed to mimic these properties: Two important examples are the Watts-Strogatz model, in which random rewiring of a small share of links in a regular graph generates a small-world network, and the Barabasi-Albert model with preferential attachment leading to a power-law degree distribution (Albert and Barabasi, 2002).

In models of social influence (see Sect. 2.4.3), graphs usually represent the social network and thus specify the possible interactions. In many models of social influence, the social network is assumed to be static. Its topology does not change over time, which means that agents interact with the same neighbors again and again (e.g., French, 1956; Friedkin, 1998). This has consequences for the dynamics on the network: If the social influence is positive, the system often converges to a global consensus. However, especially when taking longer time scales into account, social networks change and their structure evolves over time. Such changes may be modeled by a temporal network if they are independent of the dynamics (e.g., social influence) on the network (Holme and Saramäki, 2012). However, for many social processes, the structure of the social network and the dynamics on it interact. Adaptive network models therefore specify how links in the network are removed and added depending on the dynamics on the network (Gross and Blasius, 2008).

Adaptive models of social networks therefore combine two important processes: First, they capture how social structure influences the behavior, opinions, and beliefs of individual agents. This can be modeled by complementing decision models discussed in Sect. 2.3 with social influence and learning approaches in different ways (cp. Sect. 2.4.3). Second, they describe how agents' attributes and decisions drive changes in the social structure. This is specified by local update rules for the network, often assuming that agents with similar characteristics tend to form new links between each other (homophily, Axelrod, 1997), while breaking links with agents having diverging characteristics (Holme and Newman, 2006).

The combination of social influence with the updating of the network structure can result in feedback dynamics: while the social influence increases similarity, similar

agents tend to connect. This can lead to the emergence of several stable subgroups that are internally homogeneous and differ with respect to the attributes that dominate the single subgroups. This has been shown for example for opinion formation (Holme and Newman, 2006) and epidemic spreading (Gross, D’Lima, and Blasius, 2006). But adaptive network models are also used to study the evolution of network structures with game theoretic interactions in social dilemmas (Perc and Szolnoki, 2010) or coalition formation (Auer et al., 2015). To study the various effects in adaptive network models systematically, aggregation techniques using subgraphs can be used (see Sect. 2.5.3).

Networks cannot only model the interactions between individuals, the nodes can also represent collective agents on various levels of social interaction as introduced in Table 2.1. Examples for such applications are complex network structures of financial risk relations between banks, trade networks between countries, transportation networks between cities, and other communication, organizational, and infrastructure networks (Currarini, Marchiori, and Tavoni, 2016). Furthermore, approaches such as multi-layer and hierarchical networks, and networks of networks allow modeling the interactions between different levels of such systems (Boccaletti et al., 2014).

Examples for application of network approaches to social-ecological systems are rare. For instance, Berger (2001) includes a communication network in an agent-based model studying the spread of new agricultural technologies. A paradigmatic application of the adaptive network approach to social-ecological systems is introduced in Wiedermann et al. (2015). They consider a community of agents that each harvests a renewable resource. The agents interact on a social network, imitating the harvesting effort of neighbors that harvest more and may drop links to neighbors that use another effort. The interaction of the resource dynamics with the network dynamics either leads to a convergence of harvest efforts or a segregation of the community into a group with a higher and a lower effort, depending on the model parameters (see also Barfuss et al., 2017, for the effect of heterogeneity in this model).

Networks models have a huge potential to represent social ties in land-use models and study the effect of infrastructure networks, especially transportation networks, on land-use and change patterns. Furthermore, insights from the analysis of spatially embedded networks (Barthélemy, 2011) can be useful for modeling land-use systems because the spatial relations, for example of agent residency, in these systems often plays an important role. Chapter 4 of this thesis fills this research gap.

From a complex systems perspective, it is often not the individual agent behavior or local interaction that is of interest, but rather the emergent system-level dynamics resulting from these micro-level processes. Therefore, the next section discusses aggregation techniques and approaches that allow studying the resulting system-level dynamics.

2.5. Aggregation techniques for agent behavior and interactions

So far, the discussion focused on theories and modeling techniques that describe decision processes and behavior of single agents, their local interactions, and the structure of their interaction. This section highlights different aggregation methods for the behavior of an ensemble or group of agents. This section also covers interaction types that connect entire social subsystems like market mechanisms or voting procedures.

Aggregation is an important step if models shall describe collective decision making and behavior, and allow for the analysis of system-level outcomes. The techniques help to transfer models from one level (often called the micro- or local level) to a higher level (often referred to as the macro- or system level). In general, aggregation can link all levels introduced in Table 2.1.

The question how to aggregate individual and local processes to system-level phenomena is not specific to modeling human decision making and behavior. Aggregation is also an ongoing challenge in the natural sciences, for example for the description of collective motion of animals (Couzin, 2009). Assumptions about the individual behavior and the interaction of agents influence the degree of complexity of the system-level description. For instance, if the agents' resources to reach their goals do not depend upon each other, the properties of single agents can often be added up. If, on the contrary, agents influence each other's goals or interact via the environment, complex aggregate dynamics may arise.

In this section, I describe different aggregation techniques, their underlying assumptions, and how they are reflected in aggregation mechanisms. Analytical approaches generally represent groups of individual agents through some system-level or averaging characteristic, often using simplifying assumptions regarding the range of individual agents' characteristics. Simulation approaches describe individual behavior and interactions and then compute the resulting aggregate macroscopic dynamics. Computational aggregation approaches to social systems are usually named agent-based modeling. I will discuss them in the subsequent section. The various approaches are summarized in Table 2.4.

2.5.1. Representative agent approach

A widely used approach in modeling is to represent a group or population of similar agents with a "representative agent", i. e., an average agent standing for the whole group. The underlying assumption for using this approach is that heterogeneities and local interactions average out for many agents. This approach is especially used in mainstream macroeconomics for modeling the decision making of firms and households. In the following, I discuss these macroeconomic models. They are important for modeling human-nature interactions, because a major part of the relevant interaction of contemporary societies with the natural environment is related to the organization of production and consumption on markets. In macroeconomic models, one or many representative firms stand for the supply of an economy or different sectors. The

Table 2.4.: Summary table for modeling approaches to aggregation and system level descriptions.

Approaches and frameworks	Key considerations	Strengths	Limitations
Representative agent approach: represents a group by an average agent, e. g., in macroeconomic models	Which goals or preferences do representative agents have?	Allows for analytically traceable representations of groups of agents	Assumes that aggregated properties of agents are like individual ones
Aggregation via markets: equilibria in economic models	Under which conditions do market mechanisms allocate on different spatial and temporal scales efficiently? Which market imperfections are there?	Makes the connection between micro- and macroeconomics	Unique equilibrium only for very special cases
Distributions and moments: Model heterogeneous attributes and interactions of agents via statistical properties	Which heterogeneities are most important for system-level outcomes?	Systematic way to analytically treat heterogeneities	Only applicable for simple modeling approaches to behavior and interaction
Social utility and welfare: Aggregates individual utility	How is inequality evaluated? How is welfare compared between societies and generations?	Base for cost-benefit analysis, a widely applied decision model for policy evaluation	Assumes that individual utility can be compared on a common scale
Social planner and economic policy in integrated assessment models: Model ways to internalize environmental externalities	Which economic policy instruments internalize environmental externalities best? What are plausible effects of policy implementation?	Allows to determine optimal paths for reaching societal goals	Models focus on production and investment in the economy
Dynamics at the system level	Which crucial parameters in the model can be influenced by decision makers?	Allows exploring dynamical properties of the system based on system-level mechanisms	No explicit micro-foundation
Agent-based models: Simulates behavior of agents and their interactions explicitly to study emergent macro-dynamics	Which types of agents are important? How do they make decisions? How do the agents interact with each other and with the environment?	Very flexible framework regarding assumptions about decision rules and interactions	Models often with many unknown parameters, difficult to analyze mathematically

demand is modeled by one or several representative households. In the standard models, representative firms and households optimize their production or consumption taking the prices of goods and production factors as given, which mimics a situation of perfect competition. The prices of production factors are assumed to equal the value of what they can additionally produce by using one additional unit, i. e., their marginal product. In simple macroeconomic models, representative agents interact on perfect markets for all goods and input factors such as labor, physical capital, and possibly natural resources and intermediate goods. Assuming that all markets are in equilibrium (see Sect. 2.5.2), the solution of the associated optimization problem (with constraints given by a system of nonlinear algebraic equations) specifies the quantity and allocation of input factors, their prices (wages and interest rates), and the production and allocation of consumer goods. A change in one constraint can therefore lead to adjustments in all sectors and new equilibrium prices.

An important application of the representative agent approach in contemporary neoclassical macroeconomics is in dynamic stochastic general equilibrium (DSGE) models. These models account for consumption and investment decisions of economic agents under uncertainty and explore the consequences of stochastic shocks on public information or technology for macroeconomic indicators. Representative agents in DSGE models are usually utility or profit maximizers with rational expectations, i. e., they know the constraints and dynamics of the model, can form consistent beliefs about the other representative agents' strategies, and take this information into account when making decisions. Many DSGE models also incorporate short-term market frictions such as barriers to nominal price adjustments ("sticky" prices) and other market imperfections (Wickens, 2008, and Sect. 2.5.2).

Another prominent application of the representative agent approach is in economic growth models. They are used to study long-term dynamics of production and consumption. In simple growth models, a homogeneous product is produced per time interval according to an aggregate production function. A part of the output can be saved as new capital, while the remaining output is consumed. The evolution of the capital stock is given by a differential equation considering investments and capital depreciation. In the standard neoclassical growth model, the savings are endogenously determined by inter-temporal optimization of a representative household and equal investments. The household maximizes an exponentially discounted utility stream (compare Section 2.3.1), which is a function of consumption (Acemoglu, 2009). The central decision of the representative household is how much of the produced output to save to increase production in the future and therefore refrain from consuming and enjoying the output instantaneously. Such inter-temporal optimization problems can be solved either computationally by discretization in time or analytically by applying techniques from optimal control theory⁸. Besides population growth, the only long-term drivers of growth in the standard neoclassical model are exogenously

⁸Optimal control theory deals with finding an optimal choice for some control variables (often called policy) of a dynamical system that optimizes a certain objective function, using for example variational calculus (Kamien and Schwartz, 2012).

modeled increases in productivity through technological change. In contrast, so-called endogenous growth models exhibit long-run growth and endogenously account for increases in productivity, for example through innovation, human capital, or knowledge accumulation (Romer, 1986; Aghion and Howitt, 1998).

Macroeconomic models of land use describe the agricultural sector with an aggregate production function with arguments capital K , labor L , and land U . Many models use a Cobb-Douglas production function,

$$Y = A K^\alpha L^\beta U^\gamma, \quad (2.4)$$

with total factor productivity A and constant returns to scale $\alpha + \beta + \gamma = 1$ (e.g. Mundlak, 2001; Echevarria, 1998). The production function describes the maximally attainable production, given some input. A representative consumer constitutes the demand side of the economy. The production function is then analyzed in a general or partial equilibrium context (see Sect. 2.5.2). For example, in an economy with only two sectors, agriculture and industry, modeled by a representative farm and a representative firm, and the demand modeled by a representative household, increases in agricultural productivity may lead to the reallocation of labor into the industrial sector (Matsuyama, 1992).

The use of representative agents in models has been criticized for its implicit assumption that the representative agent has the same properties as an individual of the underlying group (Kirman, 1992; Rizvi, 1994): First, the approach neglects that individual agents in the represented group must coordinate, leaving out problems that arise due to incomplete and asymmetric information. Second, there is no correspondence between the individual agents' preferences and the representative agent's preferences, at least not if the agent's preferences do not satisfy very special assumptions (so-called homothetic preferences, see Varian, 2010, p.101). Third, a group of individual utility maximizers does not necessarily imply collective maximization, challenging the equivalence of equilibrium outcomes in macroeconomic compared to microeconomic models. Finally, the representative-agent approach implies that system-level phenomena can be entirely reduced to assumptions about the individual behavior, thereby neglecting the possibility that emergent phenomena arise from intra-group interaction or heterogeneity (Kirman, 2011).

Despite the deficiencies of the representative agent approach, its application to markets allows to aggregate behavior in simple and analytically tractable forms. Modelers who wish to describe economic dynamics at an aggregate level can rely on a well-developed theory that describes many economic phenomena in a good approximation.

2.5.2. Aggregation via market mechanisms

While macroeconomic models simply assume that price mechanisms work, neoclassical microeconomic models and their extensions seek to explain when and how market equilibria between supply and demand come about based on the multiple interactions

of individual agents in the market. Markets do not only mediate between the spheres of production and consumption as in macroeconomic models, they also serve as a mechanism to aggregate and coordinate agents' decisions and behavior. In markets, this coordination is mediated through prices that are assumed to reflect information about the scarcity and production costs of goods. Microeconomic analysis compares different kinds of market setting (e.g., auctions, stock exchanges, international trade) with respect to different criteria such as allocative efficiency.

Building on rational choice theory for modeling the decisions of individual agents, microeconomic models in the tradition of neoclassical economics analyze the conditions for an equilibrium between supply and demand on single markets (partial equilibrium theory) or between all markets (general equilibrium theory). The behavior of households and firms is usually modeled as utility maximization under budget constraints and profit maximization under technological constraints in the production, respectively. A central criterion for the existence of an equilibrium is that households are characterized by decreasing marginal utility, i.e., the additional individual utility derived from the consumption of one additional unit of some good is declining. Furthermore, the production functions of firms relating input factors to output are assumed to have diminishing returns, meaning that the additional production derived from an additional unit of a single input factor is declining with its absolute amount when holding other input factors fixed.

If there is perfect competition between producers, resources and goods are allocated in a Pareto-efficient way such that no further redistribution is possible that benefits somebody is possible without making somebody else worse off (Varian, 2010). It can be proven that such an economy has an equilibrium price for each good at which the market clears and supply meets demand, even though the equilibrium does not need to be unique (Arrow and Debreu, 1954). The idea of this market equilibrium can be understood by the associated prices: The rational market participants trade goods as long as there is somebody who is willing to offer some good at a lower price than a price that somebody else is willing to pay for it.

However, in markets that are dominated by a few or by very heterogeneous agents, perfect competition cannot be assumed. Price wars, hoarding, and cartel formation may occur. Such situations can be described in models of oligopoly, bargaining, and monopolistic competition. Furthermore, prices in real markets often undergo rapid fluctuations, challenging the validity of equilibrium outcomes at least in the short run. The same applies to production factors that are not fully employed like general equilibrium considerations suggest. Other deviations from market equilibria are discussed as market imperfections such as transaction costs, asymmetries in available information, and non-competitive market structures. Economic analyses help identifying which market imperfections are important to consider to model a specific market appropriately.

2.5.3. Statistical aggregation methods: modeling agent heterogeneity via distributions and moments

This section describes techniques based on statistical distributions of attributes of a group of agents that allow capturing some heterogeneities between agents. Thereby, they can mediate between microeconomic approaches with heterogeneous groups of agents and macroeconomic models. Furthermore, it introduces methods from statistical physics that account for the effect of structured interactions, as opposed to interactions in which all individuals coordinate through one or several central markets.

An ensemble of similar agents can be modeled via statistical distributions if the agents have the same type of characteristics and the characteristics differ quantitatively. For example, agents have different endowments, such as income or wealth, or are described by different parameters in utility functions. This allows to counter some of the criticism of the representative agent approach. For example, approaches to represent heterogeneous agents in DSGE models have been developed to explore the effect of unequal initial capital and asymmetric income fluctuations (Heathcote, Storesletten, and Violante, 2009). However, they pose technical challenges because they assume rational expectations, i. e., consistency of the agents' beliefs about each other's strategies. Therefore, their solution requires elaborate numerical methods.

In many contexts, agents may be better described by bounded rationality or learning theory, adapting their decision rules to changing economic circumstances (cp. Sects. 2.3.2 and 2.3.3). Techniques from statistical physics and theoretical ecology have been applied to aggregate local-level decision processes and interactions and derive system-level dynamics of simple models of adaptive agents (Castellano, Fortunato, and Loreto, 2009). For instance, the distribution of agents' properties representing an ensemble of agents can be described by a small number of statistics such as mean, variance, and other moments or cumulants. The dynamics in form of difference or differential equations of such statistical parameters can be derived by different kinds of approximations. A common technique is moment closure that expresses the dynamics of lower moments in terms of higher order moments. At some order, the approximation is made by neglecting all higher order moments or approximating them by functions of lower-order ones (see, e. g., Goodman, 1953; Keeling, 2000; Gillespie, 2009). Other statistical physics approaches use Master or Fokker-Planck equations to study Jump Markov processes derived from local interactions in the context of socioeconomic systems (Aoki, 1996; Aoki and Yoshikawa, 2006; Delli Gatti, Gallegati, and Kirman, 2000; Delli Gatti et al., 2008; Landini and Gallegati, 2014).

Structured interactions in network models can be investigated with tools from statistical mechanics, often considering statistical ensembles, i. e., sets of possible realizations of such network models, or macroscopic limits (i. e., the number of network nodes going to infinity). To aggregate simple interactions between single nodes in network models, aggregation techniques describe the changes in simple sub-graphs (motifs). These changes are usually modeled with differential equations that can be

derived from the dynamics on the network, possibly including changes in the network structure (adaptive networks, Sect. 2.4.4). In network theory, these approaches are also called moment closure, although the closure refers here to neglecting more complicated subgraphs (e.g., Do and Gross, 2009; Rogers et al., 2012; Demirel et al., 2014). For example, the simple *pair approximation* only considers different subgraphs consisting of two vertices (agents) and one link. To abstract from the finite-size effects of fluctuations at the micro-level in stochastic modeling approaches and arrive at deterministic equations, analytical calculations often take the limit of the agent number going to infinity (in statistical physics called the thermodynamic limit, cp. Reif, 1965; Castellano, Fortunato, and Loreto, 2009). Tools from dynamical systems theory such as stability and bifurcation analysis can then be used to study stable states or phase transitions on the network. Furthermore, they help explaining non-linear shifts or multi-stability of the network structure, resulting in dynamical regimes in which small changes in parameters or initial conditions have decisive impacts on the outcome. Such phenomena in social networks are often referred to as social tipping points (Bentley et al., 2014). Wiedermann et al. (2015) apply these network aggregation methods to a stylized model of a social-ecological system (see also Sect. 2.4.4).

In contrast to representative agent models, heterogeneous agent approaches, moment closure, network approximation, and other statistical techniques start from an explicit representation of local interactions to derive system-level dynamics. Such techniques are useful for the following reasons: First, they reduce computational complexity when modeling social processes at intermediate levels of aggregation, and therefore allow the investigation of meso-scale social processes. The increase in computational performance also allows a more comprehensive model analysis, e.g., of parameter dependencies and bifurcations. Second, they can provide the possibility for formal proofs, which is not possible with stochastic simulations. Third, they allow the derivation of analytical expressions of relations between model variables from the dynamic equations, which is not possible from simulation runs.

2.5.4. Aggregation of preferences: social welfare and voting

Another perspective on the representative agent approach is that its preferences describe the aggregate preferences of the represented group and not an average member. This raises the question how preferences can be aggregated. For this, the rational choice framework, which was introduced in Sect. 2.3.1 for individual decision making, can be expanded to model the behavior of social collectives at different levels introduced in Table 2.1. The concepts of such an extension are often collected under the label of social choice theory, which studies the aggregation of individual preferences to social welfare, a measure of collective desirability of an outcome of a collective choice or action.

The aggregation of utility across individuals into a social welfare function needs the crucial assumption that utility is comparable between agents. When only ordinal (e.g., binary) preference relations are given, general statements about aggregated

preferences are very limited (Arrow, 1950). Therefore, a cardinal (scale-measurable) unit of utility (“util”) is introduced representing an amount of satisfaction, happiness, or often simply a monetary value.

The simplest way of aggregating individual utility is by a linear and inequality-neutral welfare function, averaging over individual utilities in a group. However, this raises the issue that a drop in collective welfare resulting from an agent’s decrease in utility can be compensated by increasing the utility of another agent. This critique is sometimes countered by making the additional assumption that groups can redistribute utility internally.

However, aggregation techniques have been proposed that inherently account for inequality between agents and thereby do not allow that utility can be completely substituted between individuals. Examples of such approaches are the Gini-Sen welfare function, the Atkinson-Theil-Foster welfare function, and the egalitarian welfare function, which takes simply the minimum of utility of the group’s members as the social welfare measure for the entire group (Dagum, 1990). Such techniques can also be understood to represent the preference of individuals for equality between group members. In economic contexts, welfare functions are often based on monetary values such as wealth, income, and total value of consumption. When the group composition or its size change over time (e.g., in intergenerational models), the definition of suitable measures of social welfare raises even more intricate ethical questions (Millner, 2013).

A social welfare function allows choosing the optimal option of a decision problem. For example, social welfare functions are used to evaluate which policy of a bundle of options is optimal. In economic analysis, welfare maximization is often reduced to cost-benefit analysis by using a linear social welfare function and identifying utilities simply with monetary values (Feldman and Serrano, 2006). An alternative to such policy evaluation tools is multi-criteria decision making (Huang, Keisler, and Linkov, 2011). However, cost-benefit analysis remains one of the most applied decision models to normatively evaluate policies and can therefore – under certain circumstances – be used to descriptively model decisions of governments.

Some models of deforestation analyze the trade-off between productive use of land and forest conservation from the perspective of social welfare (Satake and Rudel, 2007; Barbier and Tesfaw, 2015). In the context of land use, such models investigate whether the transition from deforestation to reforestation follows optimal paths and determine the effectiveness of different policies to reach optimal outcomes.

Voting and bargaining theory are sub-branches of game theory that focus on the rules and processes that determine how a joint decision or action of a group come about based individual choices of the group’s members. They study the design of voting protocols, i.e., formal rules that determine a collective choice from individual ones and therefore constitute aggregation mechanisms for individual (and possibly heterogeneous) preferences. Depending on the voting protocol, larger subgroups can dominate the decision (e.g., with majority vote) or the group may reach a compromise between subgroups with different preferences (cp. Heitzig and Simmons, 2012). The

outcomes depend crucially on the individual's strategies to use their vote and their beliefs about the other agents' strategies.

The approaches of social welfare theory are applied in the context of environmental policy mainly in integrated assessment models, which will be the focus of the next subsection.

2.5.5. Application of welfare theory in integrated assessment models: social planner and economic policy

Integrated assessment models (IAMs) comprise a large modeling family that combine economic with environmental dynamics. The majority of currently used IAMs draws on ideas from environmental economics. Using the concept of environmental externality, they evaluate the extraction of exhaustible resources, environmental pollution, and overexploitation of ecosystems economically. Externalities are benefits from or damages to the environment that are not reflected in prices and affect other agents in the economy (see, e.g., Perman et al., 2003). These models therefore help to assess economic policies that tackle environmental problems.

State-of-the-art global IAMs combine macroeconomic representations of sectors like the energy and land system with models of the material processes and environmental impacts of these sectors. For example, CO₂ emitted from burning fossil fuels is linked to economic production by carbon intensities and energy efficiencies in different production technologies. IAMs often model technological change endogenously, for example with investments in research and development, and learning-by-doing (i.e., decreasing costs with increasing utilization of a technology). Because of the possibility to induce technological change, the models capture path-dependencies of investment decisions. Many IAMs take the perspective of a social planner, who makes decisions on behalf of the society by optimizing a social welfare function (see Section 2.5.4). It is assumed that the social optimum equals the perfect market outcome with economic regulations that internalize all external effects (e.g., emission trading schemes).⁹

IAMs are mostly computational general or partial equilibrium models, describing market clearing between all sectors or using exogenous projections of macroeconomic variables (see Sect. 2.5.2). They also differ with respect to inter-temporal allocation: While inter-temporal optimization models use discounted social welfare functions to allocate investments and consumption optimally over time, recursive dynamic models solve an equilibrium for every time step (Babiker et al., 2009). Furthermore, IAMs are designed for either (1) determining optimal environmental outcomes of a policy by making a complete welfare analysis between different policy options or (2) evaluating different paths to reach a political target with respect to their cost-effectiveness (Weyant et al., 1996). For example, many IAMs of the energy system have emission targets for climate policy as constraints in their optimization procedure and determine the best way to reach them (Clarke et al., 2014).

⁹This argument is based on the second fundamental theorem of welfare economics, see for example Feldman and Serrano (2006, pp. 63–70).

For the analysis of land-use, IAMs combine geographical and economic modeling frameworks, using welfare maximization or cost minimization to calculate the optimal allocation of land uses and land-use change (Lotze-Campen et al., 2008; Hertel, Rose, and Tol, 2009; Havlík et al., 2011). These models are used for example to investigate the competition between different land uses and trade-offs between agricultural expansion and intensification. The optimization allocates land uses regionally or globally between different areas, only constrained by environmental factors such as soil quality, climatic conditions, and water availability, as well as economic conditions and protection policies.

Many IAMs focusing on land-use change build on location theory from economic geography, often using variants of the bid-rent or von Thünen model (Puu, 2003, Ch. 5). These models assume that the land use is allocated among different locations such that the land rent is maximized. In the basic model, the rent R_j of a patch of land at location j is given by the revenue from selling the agricultural product (or other good) produced at this location Y_j on a central market at price p . From this, the production cost c_p and transport cost are subtracted:

$$R_j = Y_j(p - c_p - c_T d_j), \quad (2.5)$$

where d_j is the distance of the location from the market and c_T is the transport cost per distance and transported unit. Because different land-use activities have different yields, production, and transport costs, and prices react to the supplied quantities, the maximization of land rents over different land-use activities at different locations leads to an optimal allocation of land uses between locations. This model can explain empirical land-use patterns if the transport costs are sufficiently high compared to other costs. While the original model assumed uniformity of soil quality and topography and only one mode of transportation, there are many extensions taking all kinds of geographic heterogeneities into account. Bid-rent models have also been applied to the Brazilian Amazon to study deforestation and discuss policy options (see Walker, 2004; Angelsen, 2010; Bowman et al., 2012; Walker, 2014).

The results of integrated assessment models are not meant as predictions of the future development of the economy, energy and land system, but rather as a normative exploration of different technically and economically feasible possibilities. Furthermore, they have the purpose to help policy makers assessing different policy instruments, which help to reach the environmental policy goals, and their trade-offs. While the decision about the policy is exogenous to the model, the investment decisions within and between sectors are modeled as a reaction to the political constraints. However, most IAMs do not account for possible changes on the demand side, e. g., through changes in consumer's preferences for green products.

2.5.6. System dynamics, stock-flow consistent and input-output models

This final subsection discusses modeling approaches to human-nature interactions without explicit micro-foundations. Decisions in such models are not modeled explicitly with one of the options discussed in Sect. 2.3 but, as policy decisions in integrated assessment models, through the construction of different scenarios for the evolution of crucial exogenous parameters in the model. However, they comprise an important model class and deserve a discussion because of the multiple applications on questions of interacting social and ecological systems.

System dynamics models describe system-level dynamics with ordinary differential equations or difference equations of aggregate variables to explore possible future developments. The equations are often built on stylized facts about the dynamics of the underlying subsystems and are linked by functions with typically many parameters. System dynamics models are used to develop scenarios based on different sets of model parameters and assess system stability and transient dynamics of a system. In comparison to equilibrium approaches, system dynamics models capture the inertia of a system at the cost of a higher dimensional parameter space. This can lead to complex dynamics, e. g., oscillations and overshooting. Global system dynamics models describe global production, population, and crucial parts of the environment as well as their dynamic interactions. They can be very detailed like the World3 model commissioned by the Club of Rome for their famous report on “Limits to Growth” (Meadows et al., 1972; Meadows, Randers, and Meadows, 2004) or the International Futures model (Hughes, 1999). Subsystems of such models comprise the human population (sometimes disaggregated between regions and age groups), the energy sector, as well as the state of the environment (pollution and resource availability). The agricultural sector in those models aggregates different processes like land expansion, erosion and management to describe the dynamics of land fertility and food production in a stylized way. There are also simpler models that break down the global environmental and socioeconomic dynamics to even fewer variables (e. g., Kellie-Smith and Cox, 2011).

Systems dynamics models have also been developed for regional contexts. Brander and Taylor (1998) present a model of natural resource use on the Easter Island, reproducing the population overshoot and environmental degradation that might have contributed to the decline of the local culture. The model by Portela and Rademacher (2001) determines deforestation in the Amazon by activities of ranches and farms depending on soil quality, erosion, and land speculation.

Other system-level approaches to macroeconomic modeling emphasize self-reinforcing processes in the economy and point to positive feedback mechanisms, resulting in multi-stability or sometimes even instability of the economy (e. g., increasing returns to scale in production and self-amplification of expectations during economic bubbles). For example, post-Keynesian economists use stock-flow consistent models to track the complete monetary flows in an economy in which low aggregate demand can lead to underutilization of production factors. In these models, a social accounting

matrix provides a detailed framework of transactions (e. g., monetary flows) between households, firms, and the government, which hold stocks of assets and commodities (Godley and Lavoie, 2007).

Input-output models track flows to much more detail between different industries or sectors of production (Leontief, 1986; Ten Raa, 2005; Miller and Blair, 2009). Each industry or production process is modeled by a Leontief production function, which is characterized by fixed proportions of inputs depending on the available technology. Such models are used for instance to explore how changes in demand would lead to higher-order effects along the supply chain. Regional input-output models also account for spatial heterogeneity and are used for example to evaluate possible impacts of extreme climate events on the global supply chain (Bierkandt et al., 2014).

While the approaches discussed above focus on the monetary dimension of capital and goods, models from ecological economics (Bergh, 2001) track material flows or integrate material with financial accounting. For example, input-output modeling has been extended to analyze the industrial metabolism, i. e., the material and energy flows and its environmental impacts in modern economies (Fischer-Kowalski and Haberl, 1997; Ayres and Ayres, 2002; Suh, 2009). Regionalized versions of such models can for instance be used to estimate the environmental footprint that industrialized countries have in other regions (Wiedmann, 2009). In the emerging field of ecological macroeconomics (see Hardt and O'Neill, 2017, for a detailed review of modeling approaches), stock-flow consistent and input-output models have been combined into one framework tracking financial as well as material flows (Berg, Hartley, and Richters, 2015). Other ecological models use the flow-fund approach by Georgescu-Roegen (1971) or combine it with stock-flow consistent modeling approaches (Dafermos, Nikolaidi, and Galanis, 2017). While the flow concept refers to a stock per time, a fund is the potentiality of a system to provide a service. The important difference lies in the observation that a stock can be depleted or accumulated in one time step while a fund can provide its service only once per time step. This distinction reflects physical constraints on the production process that have important consequences for modeling the social metabolism.

To use approaches that only consider the system level for modeling the impact of humans on the natural environment, they could be combined with approaches that model the development of new production technologies. This would allow investigating how the deployment of new technologies is affected by decisions at different levels (consumers, firms, and governments). Even if this integration with decision models may prove difficult, the approaches discussed in this section can help linking social and environmental dynamics in new ways, providing an important methodology to model human-nature interactions at an aggregate level.

2.6. Computational agent-based models of social-ecological systems

Agent-based modeling is a computational modeling approach that explicitly simulates heterogeneous and interacting agents of a social or social-ecological system. Agent-based models¹⁰ (ABMs) are used to investigate the emergence of system-level patterns and dynamics based on local processes and interactions between autonomous agents (Epstein, 1999; Tesfatsion, 2006; Hamill and Gilbert, 2016). The local interactions that influence the agents' decisions can be structured for example by their embedding in geographic space or by social networks (Alam and Geller, 2012). The resulting system-level dynamics are often non-linear and can be qualitatively very different from individual behavior.

The concept of agents in ABMs comprises individual and collective human agents (including households, firms, and other organizations), but the notion is often extended to non-human entities such as animals, animal groups, and vegetation. In ABMs, types of agents may be distinguished according to their attributes, roles, and decision making models. Heterogeneity within one type can be represented by quantitative differences in attributes of agents, for example by their possession of different forms of capital. Empirically driven ABMs classify types of agents by their attributes and decision heuristics that are derived from empirical data. The data is usually obtained via interviews or surveys (Smajgl and Barreteau, 2014). In contrast, the agent typology can also be based on theoretical considerations, grouping agents according to their attributes, interactions, and roles. A promising theoretical approach are agent-functional types, which has been proposed for modeling the adaptation and change of land-use practices (Murray-Rust et al., 2014; Arneth, Brown, and Rounsevell, 2014).

To model the decision making of agents, ABMs allow applying all approaches discussed in Sect. 2.3 or other decision functions and formal rules derived from empirical evaluations. While decision making theories beyond rational choice theory are still under-represented in the literature, their share has increased. However, many decision theories need further development and formalization to include them into ABMs (Schlüter et al., 2017).

Agent-based approaches can also be applied without explicitly modeling each individual agent of the system. Instead, it is often sufficient to model a representative statistical sample of agents that depicts the heterogeneities of the underlying population. Stochasticity in the dynamics of environmental or social processes can also be used to represent uncertainty in ABMs.

ABMs are applied in many fields. In the last decades, they are increasingly used in the social sciences, e. g., sociology (Macy and Willer, 2002), economics (Tesfatsion, 2006; Heckbert, Baynes, and Reeson, 2010; Hamill and Gilbert, 2016), political science (Marchi and Page, 2014), and the cognitive sciences (Conte and Paolucci,

¹⁰In some scientific communities, ABMs are called multi-agent simulations (MAS, Bousquet and Le Page, 2004) or individual-based models (especially in ecology, Grimm and Railsback, 2005).

2014). Applications have also been pioneered in ecology (Grimm and Railsback, 2005).

Furthermore, ABMs have been a major theoretical tool to understand human-nature interactions in social-ecological systems (Schlüter et al., 2012; An, 2012) and land-use systems (Matthews et al., 2007). Besides agent behavior and interaction, ABMs of social-ecological systems represent dynamics of the biophysical environment that are relevant for the agents' decision making. Thereby, they capture feedbacks between human decision making and environmental processes.

Most ABMs in the context of land use and agricultural economics are developed for local or regional studies, taking into account local specificities and fitting behavioral patterns to data acquired in the field (Parker et al., 2003; Matthews et al., 2007). They apply different behavioral theories: While many models describe the adaptive capacities of rational or boundedly rational agents, only few include learning (Groeneveld et al., 2017). Some studies combine ABMs with cellular automaton models describing the dynamics and state of the physical land system (e. g., Heckbert, 2013). In these ABMs, the spatial embedding of agents plays an important role (Stanilov, 2012).

An example for the application of ABMs to land-use systems is the model in Martin et al. (2016). It describes cattle ranchers that move their livestock between patches of grassland of a commonly used landscape of meadows. Overgrazing in one year decreases feed availability in the following year because of the underlying biomass regrowth dynamics. Agents decide how many cattle to graze on a patch based on their individual goals, needs, information on the state of the grassland, beliefs about the future, and interactions with other ranchers. The model tracks the interplay and success of different land-use strategies on common land and assesses their vulnerability to shocks such as droughts.

ABMs have also been used to simulate deforestation dynamics in the Amazon. Mena et al. (2011) design a detailed ABM of household farms in the Ecuadorian Amazon, including complex land-use decisions, demography, and migration. Using geographic and socioeconomic data, the model reproduces demographic and land-use change patterns and thereby fosters the understanding of relations between patterns and the underlying social and environmental processes.

ABMs of land use have not only been used to increase system understanding, but also to investigate the effects of different policy interventions. For example, the model by Andersen et al. (2017) focuses on deforestation and subsequent land use of a small community in the Bolivian Amazon. The authors implement different policy measures in the model, study their effect on deforestation outcomes, and conclude that the sequencing of policy plays an important role for the outcomes.

As discussed throughout this section, agent-based approaches are very flexible and can be applied to a variety of different systems. But they also have limitations. First, they are often characterized by a high complexity and dimensionality of state and parameter space. Thus, they require high computational capacities for model analysis and sophisticated techniques to understand the dynamics beyond single trajectories. Second, the model mechanisms are difficult to trace in the black box of a

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computational model, which is why the results of ABMs can be difficult to interpret. There are various techniques available for comprehensive model analysis (Lee et al., 2015), but systematic model exploration is not very common and mostly limited to sensitivity analysis of crucial parameters. Furthermore, numerical analyses alone cannot provide mathematically sound proofs of relationships between model variables. Third, there are efforts to make model descriptions of ABMs comparable (Grimm et al., 2006). But the comparison of model results remains difficult because there is a lack of standardization for the representation of process and the evaluation of outputs (Hamill and Gilbert, 2016, p. 239).

Nevertheless, ABMs are an important modeling tool for social systems in which the diversity of behavior is decisive for system-level outcomes and therefore cannot be represented by a single representative agent or a distribution of agents' properties as, for example, in many macroeconomic models (cp. Section 2.5.1). Agent-based approaches allow addressing questions of interactions across levels, for instance how patterns of land use emerge from interdependent regional and local land-use decisions which are in turn constrained by the emerging system-level patterns. Furthermore, they allow capturing the adaptation of behavioral strategies to environmental changes such as climate impacts on water availability and agricultural yields. Therefore, ABMs are an appropriate and promising tool to study heterogeneous agents and their interaction with technological and environmental changes in social-ecological systems (Farmer et al., 2015).

For these reasons, I decided to switch from the rather data-driven approach presented in Chapter 3 in this thesis to an agent-based approach, which is able to incorporate decision making directly, as outlined in Chapter 4. Before proceeding with these parts of the thesis, the following sections discuss principles that can guide model choices and provide reflections on differences between natural and social systems, which make modeling of social systems a challenge.

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The previous three sections showed that there is a diversity of approaches to model individual human decision making and behavior, to describe interactions between agents, and to aggregate these processes. It also highlighted that these approaches are linked to different assumptions and theories of human behavior. While some modeling techniques are compatible with many theories of human behavior and decision making, and can thus be used with a variety of assumptions, other techniques only work with very specific assumptions.

The review furthermore showed the variety of disciplines and fields developing and applying such models. During the research for this chapter, I found considerable differences in the terminology used to describe the different approaches and their underlying theories. Sometimes, the same terms are used to describe quite separate

varieties of an approach in different fields. Then again, different terms from separate fields may refer to very similar approaches.

Many of the techniques reviewed here are economic modeling techniques. This has two simple reasons: First, economics is the social science discipline that has the longest and strongest tradition in formal modeling of human decision making. Second, economics focuses on the study of production and consumption as well as the allocation of scarce resources. In most industrialized countries today, a major part of human interactions with the environment is mediated through markets, central in economic analyses. This review aimed to go beyond the narrow framing characterizing many economic approaches, while at the same time not ignoring important economic insights. For instance, consumption and production decisions do not only follow purely economic calculations but are deeply influenced by behavioral patterns, traditions, and social norms (The World Bank, 2015).

Modelers must choose carefully which assumptions about human behavior and decision making are plausible for specific research questions and the associated modeling purpose (e.g., system understanding, policy evaluation, or prediction). Modeling choices require a constant interplay between model development and the research questions that drive it.

In the following, I discuss some general considerations regarding the choice of modeling approaches for individual decision making, interactions, and aggregation. Then, I discuss some guiding principles for choosing appropriate techniques, that are similarly applied in natural science modeling. The section concludes with reflections on differences between natural and social science modeling and the resulting challenges for modeling social systems.

2.7.1. Guiding principles for choosing modeling approaches

Concerning the behavior and decisions of individual agents, I outlined three important determinants in decision models: motives, restrictions, and decision rules. Because there is no universal theory of human decision making, modelers must make assumptions about each of these three determinants appropriate for the context of the modeled decision situation. For instance, in a competitive situation the assumption that agents only consider personal incentives is suitable whereas a situation characterized by social cooperation would require that agents account for other criteria, such as a desire for a fair distribution (Opp, 1999). Decision experiments show that the relevance of motives is not stable over time and that a slight shift in the framing of decision problems can change the perceived importance of goals (Tversky and Kahneman, 1985). The choice of decision rules has to suit the availability of information in a situation, and the importance and urgency of the decision. For instance, optimization over utilities of all possible choices may describe major decisions well, if agents have access to all relevant information and the time to compare alternatives. In contrast, situations of limited information and time may be better described by simple decision rules like heuristics. In some situations, the combination of different decision rules captures the decision-making process best (Camerer and Ho, 1999).

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For choosing a suitable model of agent interactions, modelers can consider the type and setting of interactions, the assumptions that agents make about each other, the influence they may exert on each other, and the structure of interactions as determining criteria. For example, interactions in competitive environments will probably follow strategic considerations and only lead to cooperation if this is individually beneficial. In less competitive settings, where social norms and traditions play a crucial role, agents can be better described as behaving adaptively, e. g., imitating other agents. Furthermore, social settings might imply that agents communicate opinions or beliefs, influencing each other's decisions in this way. Adaptive behavior and social learning can also be a good approach to describe the evolution of cultural norms or traits.

To find an appropriate aggregation technique for agent behavior and interaction, the properties of mediating economic and political institutions, decision criteria for collective agents, heterogeneity of modeled agents, and relevant time and spatial scales for system-level outcomes must be taken into account. Modelers must choose the aggregation method that fits the real-world systems of interest and properly describes the studied aggregation mechanisms (e. g., market mechanisms or voting procedures) and system-level dynamics. Whether the collective behavior of many agents is better described by a representative agent as in macroeconomic models, a distribution of agent characteristics, or many diverse individuals as in ABMs, depends on the importance of agent heterogeneity and interaction structures. The choice of the aggregation approach is furthermore crucial for the purpose of the model because of the different normative or descriptive assumptions they imply. For example, a comparison between agent-based approaches and macroeconomic integrated assessment models shows that the former are well suited to increase system understanding and investigate the effects of local policy interventions, while the latter are more appropriate to evaluate and compare different system-level policies. The choice of aggregation technique determines which characteristics and processes of the system are explicitly modeled and which assumptions are only implicitly underlying the specific structure of the model.

In some cases the local structure of interaction is important for the overall outcomes of the studied system. This requires a gridded or networked approach to represent the heterogeneity of interactions. Otherwise, a mean field approximation of interactions between agents or other model components can be justified. For example, the interactions between two groups of different types of agents may be modeled explicitly on a social network, or it might be sufficient to consider a mean interaction term between the two groups. Whether the interaction structure matters can rarely be answered a priori but is the result of a comparison between an approximation and an explicit simulation. Modelers of natural systems face similar choices, for example when deciding whether to model the interaction between the ocean and atmosphere locally or via a mean field.

For the choice of a suitable aggregation technique, modelers also must decide on the level of detail to describe the system. The choice depends on the expected importance of interactions and heterogeneity in the set of system constituents for the model purpose and the research question. For instance, if the goal is to predict the future

development of a system, a system-level description could already be sufficient. In contrast, a more detailed model is needed for understanding the mechanisms that explain these outcomes in terms of the interactions of different system constituents. Likewise, for a normative model aiming to identify the action that maximizes social welfare, an intermediate level of detail could be appropriate, taking only specific heterogeneities of agents into account. For example, a model of social dynamics may either use a representative agent approach or explicitly model heterogeneous agents in an agent-based model. An analogous example from ecological modeling is the choice between the simulation of representative plant types or individual adaptive plants of a population to model an ecosystem.

In general, the evaluation of time scales can help in many of the above-mentioned modeling choices to decide whether social processes and properties of socioeconomic units should be represented as evolving over time, can be fixed or must not be explicitly modeled for a suitable system-level description. For example, general equilibrium models can be a good description if the convergence of prices happens on fast time scales and market imperfections are negligible. Dynamical system models, on the contrary, may be more appropriate to describe systems with a high inertia that operate far from equilibrium due to continuous changes in system parameters and slow convergence. An example from global circulation models in environmental physics is the CO₂ concentration: It can be assumed to be well-mixed for the atmosphere. But assuming this for the ocean with its slow convection would considerably distort results on politically relevant time scales (Mathesius et al., 2015). A decisive question is therefore if the time scales of processes in the system allow a separation of scales. For instance, this is possible if the local interactions are some orders of magnitude faster than changes in system parameters or boundary conditions. Similar considerations apply for spatial scales.

A general problem for selecting modeling approaches originates from frequent discrepancies between technical and content-related considerations. Assumptions are often chosen due to their mathematical convenience, e. g., mathematical simplicity and tractability. This can be problematic if the relation of the assumptions to the modeled entity remains unexplained. However, integrating the most plausible assumptions often comes at the expense of analytical clarity and simplicity. Therefore, assumptions must balance the trade-off between plausibility and technical practicality of their implementation.

2.7.2. Differences between natural and social science models

As the discussion above shows, there are several similar criteria regarding the choice of modeling techniques and assumptions in models of natural and social systems. However, there are also fundamental differences between these systems that pose a big challenge for an informed choice of modeling techniques. Natural science models can often build on physical laws describing local interactions that can be tested and scrutinized. This can result in very complex system-level dynamics with high uncertainties. But models including human behavior must cope with the variety

of disputed accounts of basic motivations in human decision making. And these accounts change over time as societies evolve and humans change their motivations and actions because of newly available knowledge and technologies.

This can lead to a crucial feedback between the real world and models: Agents (e.g., policy makers) may decide differently when they take the information provided by model projections into account. Modeling choices regarding human behavior may eventually change the behavior. This aspect of human reflexivity makes models of human societies fundamentally different from models of the physical world because humans are not only scientific observers but also active parts of social systems (Soros, 2013). In response to this, Beinhocker (2013) proposes to consider social systems as complex reflexive systems, which are characterized by agents that have an adaptive internal model that specifies how their actions will influence the environment. In such a system, knowledge and action become interdependent (Davis, 2013).

The reflexive aspect of human decision making and its consequences for social modeling are closely related to the crucial but often confused distinction between normative and descriptive model purposes. For example, models that optimize social welfare usually reflect the goal that a government should pursue, and therefore have a normative purpose. But if this model is used to guide policy making while considering the actual and perceived control of policy makers, and considers the effect of compromises between different interest groups, it could also describe their behavior. However, this is rarely the case, as projections with integrated assessment models show. This already illustrates the intricate interconnections between normative and descriptive assumptions in decision modeling that modelers should be aware of.

The distinction between normative and descriptive analyses is further complicated by the observation that the same assumption may be understood in one model as a descriptive (positive) statement whereas in another model it may be meant as a prescriptive (normative) one. For example, in a model of agricultural markets, the assumption that big commercial farms maximize their profits might be a reasonable descriptive approximation. However, in a model that investigates how small farms could survive under competitive market conditions, the same assumption gets a strong normative content. Therefore, it is important that modelers get the normative status of the assumptions they use in their models straight.

To conclude, I have shown the crucial differences between social and natural science models regarding their relation between the studied object and the investigating subject. The consequences of human reflexivity have to be considered when designing models of social systems and interpreting their results.

2.8. Summary

This chapter reviewed modeling approaches that can be used to model human-nature interactions, the mathematical techniques they use, and underlying theories of human behavior as well as applications in land-use models. Table 2.5 summarizes the modeling approaches regarding the proposed three categories. First, individual

Table 2.5.: Collection of questions to guide the choice of modeling approaches and assumptions.

Category	Important modeling questions
Modeling individual decision making and behavior	<p>Which goals do agents pursue?</p> <p>Which constraints do they have?</p> <p>Which decision rules do agents use?</p> <p>How do agents acquire information and beliefs about their environment?</p>
Modeling interactions between agents	<p>Do agents interact in a competitive environment or are interactions primarily governed by social norms?</p> <p>What do agents assume about each other's rationality?</p> <p>Do agents choose actions strategically or adaptively?</p> <p>How are agents influenced by others regarding their beliefs and norms?</p> <p>Which structure do the interactions have and how does the structure evolve?</p>
Aggregating behavior and modeling dynamics at the system level	<p>Are decisions aggregated through political institutions (e. g., voting procedures) or markets?</p> <p>According to which criteria do policy makers decide and which options for intervention do they have?</p> <p>Is the heterogeneity of agent characteristics and interactions important?</p> <p>Which macro-level measures are dynamic and which fixed?</p>

decision modeling focuses on decision processes and the resulting actions and behavior of autonomous agents, making assumptions about the determinants of choices. Second, interaction models capture how decisions are made when outcomes depend on the decisions of several agents. Such approaches also describe the agents' influence on each other regarding decision criteria such as beliefs, values, or arguments. Third, modeling techniques that aggregate agent behavior and interactions are crucial for studying the emergent system-level patterns and dynamics. They combine ingredients of the first and the second categories.

In addition, Table 2.5 collects important questions to guide the appropriate choice between the discussed model assumptions and approaches. These questions include the levels of description, the time scales, and the purpose of the model. The latter can lead to difficulties with the amalgamation of normative and descriptive modeling assumptions and must deal with the implications of human reflexivity.

To find the right assumptions for a specific context, modelers can build on and consult existing social-scientific research. Nevertheless, some of this research is difficult to access because varying usage of notions in different disciplines and opposing schools of thought often leads to ambiguities. Furthermore, modelers have to be careful with generalizing single case studies from their local or cultural context. In case of doubt, modelers can team up with social scientists to conduct empirical research in the specific situation needed to select the appropriate approach. The selection of a modeling technique compatible with the chosen assumptions also must consider the limitations of approaches for meaningful research questions and analyses.

This review of modeling approaches provides a basis for the design of an agent-based model of cattle ranching in frontier regions of the Amazon introduced in Chapter 4. The discussion above has shown the many possibilities of modelers to represent social-ecological systems like the land system. Therefore, it is important to develop specific questions that guide model composition first. For doing so, I had a closer look at Amazon land-cover data. The following chapter presents a study that analyzes this data aiming at a better understanding of post-deforestation land-use patterns and dynamics in the region.

Chapter 3.

Land-cover dynamics and patterns in the Brazilian Amazon

3.1. Introduction

After discussing how to model human-nature interactions in general and in the land-system context in specific, I provide now a detailed perspective on the example of Amazon deforestation and land-use. In this section, I present a systematic analysis of the land-cover dynamics following deforestation by applying methods from statistical physics and network theory to get a better understanding of the processes leading to deforestation. This work is mainly based on Müller-Hansen et al. (2017a, P3). At the end of the chapter, I discuss how the obtained data and analysis can be used to parameterize simple Markov-chain models that capture the transitions between different land uses. I discuss the resulting projections for land-use types and their limitations, which led me to develop an agent-based model of Amazon deforestation and land-use (Chapter 4).

As mentioned in Sect. 1.3, the spatial patterns of frontier development in the Amazon have been divided into three stages, corresponding to three regions (Becker, 2005). In the remote areas in the west of the Brazilian Amazon, the forest is mostly undisturbed. The already consolidated areas mainly lie inside the so-called arc of deforestation between the south and the east of the Amazon basin (see Fig. 1.4). The frontier regions, where most of the deforestation occurs, are mostly located along the main roads into the forest and the edge of the arc. This spatial partition is used in the literature to analyze inter-regional differences in the Brazilian Amazon. For example, Aguiar, Câmara, and Escada (2007) determine different drivers of deforestation and find that the importance and combination of factors such as protected areas, distance to roads, and access to markets differ between the three partitions. However, they take the spatial partition as given and do not derive it directly from data or relate it to land-use and land-cover transitions.

This chapter explores methods to detect patterns of land-cover dynamics in large-scale high-resolution data sets derived from remote sensing products using transition matrices and cluster analysis. Such a spatially detailed data set is available for the Brazilian Amazon (Almeida et al., 2016). The proposed method allows classifying the region into distinct clusters according to observed land-cover changes in smaller subregions. For this, I draw on the theory of Markov chains that has been used in the

context of land-system science to describe and analyze land-cover dynamics (Bell and Hinojosa, 1977; Baker, 1989; Fearnside, 1996). Markov chains are stochastic systems described by transition probabilities between discrete states. In this application, these states represent specific land-cover types, encoded in the data as different classes. While a Markov chain can be used to describe the stochastic dynamics of a single patch of land, we can interpret an ensemble of such chains as a representation of a collection of land patches.

In the past, most studies using Markov-chain analysis focused on small regions due to limited data availability. Modern geographic information systems (GIS) enable the detection of land-cover changes at an unprecedented scale using satellite images (Lu et al., 2004). Automated algorithms can classify the land cover of vast regions. Furthermore, it is possible to compare the land-use dynamics between different subregions and find differences and similarities based on consistent datasets. For example, Levers et al. (2015) combined different sources of land-use indicators and used self-organizing maps to identify archetypical land uses and regions with similar land-use change in Europe.

This study uses transition matrices as a descriptor of aggregate land-cover dynamics estimated from high-resolution land-cover data for 3 time slices of land-cover over 6 years in the Brazilian Amazon. Markov-chain analysis has so far not been applied to investigate interregional heterogeneity of land-cover dynamics. This chapter explores this idea by comparing transition matrices from different subregions in the Brazilian Amazon to identify patterns of similar land-cover dynamics. Using the new method, I investigate the hypothesis that different land-cover dynamics can be identified by the characteristics of their transition matrices and a partition of subregions, for example into remote, frontier and consolidated areas, can be detected in the data. I apply different clustering algorithms to test the robustness of the resulting geographic partition. This allows judging whether the obtained clusters do form distinct modes of land-use change or whether the distinction between different clusters is a rather gradual one.

A detailed analysis of the land uses following deforestation are a prerequisite to understand deforestation dynamics and its underlying drivers. By using the available large-scale data sets, it is possible to compare the dynamics between subregions and identify underlying patterns. Furthermore, a systematic analysis of the entire Brazilian Amazon region can help to identify spatial effects such as indirect land-use change (Barona et al., 2010).

In the remainder of the chapter, I describe the data used for this analysis (Sect. 3.2) and present in detail the proposed method (Sect. 3.3). Section 3.4 discusses the results of the analysis, pointing to possible interpretations but also restrictions of the method. Section 3.5 presents and discusses projections for future land-cover evolution using the presented data to parameterize different Markov models of land-cover change in the Amazon. Section 3.6 summarizes the results.

3.2. Data: Maps of land-cover in the Brazilian Amazon

For this study, I use land-cover maps of the Brazilian legal Amazon (cp. Fig. 3.1) produced by the TerraClass project (INPE and EMBRAPA, 2016) for the years 2008, 2010, and 2012.¹¹ The land-cover maps are derived from high-resolution Landsat-5 thematic mapper (TM) and MODIS imagery using a mix of techniques including supervised learning and classification by spectral properties of different land-cover types and their annual variations (for details, see Almeida et al., 2016; Coutinho et al., 2013). The maps consist of polygons that represent patches of land attributed to one of 16 specific land-cover types (see Table 3.1). The maps are based on the PRODES project that distinguishes between forest, patches not belonging to the rain forest biome (mainly savanna), hydrography (i.e., lakes and rivers), and deforested patches larger than 6.25 ha (PRODES, 2018). TerraClass further specifies the land-cover of formerly deforested areas according to 12 types including different kinds of pasture land, secondary vegetation, and annual crops (see Table 3.1).

The TerraClass data has been evaluated in Coutinho et al. (2013) using the method described in Congalton and Green (2009). Considering a very small sample of the data set, they found up to 58 % commission and up to 34 % omission errors, which means that the detection accuracy is not very high. However, due to the small sample size and the restriction to one region, the evaluation is not representative.

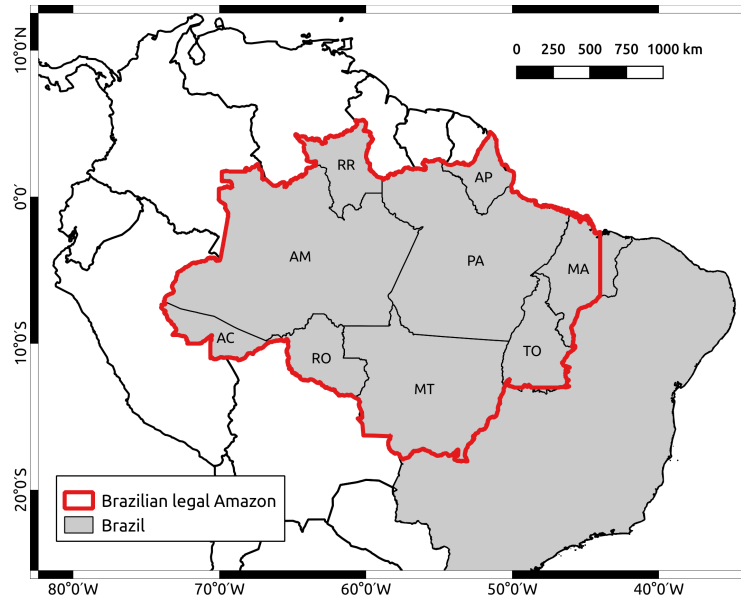


Figure 3.1.: Map of the Brazilian legal Amazon and its nine federal states: Acre (AC), Amapá (AP), Amazonas (AM), Maranhão (MA), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), and Tocantins (TO).

¹¹After publication of the paper P₃, on which this section is based, two further maps were made available for 2004 and 2014.

Table 3.1.: Overview of land-cover classes in the TerraClass data set, their assignment to simplified classes used in this chapter, and percentage of total areas (the values are rounded for better readability, therefore the numbers may not exactly sum up to 1).

#	TerraClass category	Simplified classes	Percentage of total area		
			2008	2010	2012
01	Annual crops	Annual crops	0.70	0.80	0.82
02	Mosaic of uses	Other	0.49	0.36	0.19
03	Urban area	Other	0.076	0.089	0.110
04	Mining	Other	0.015	0.020	0.021
05	Herbaceous pasture	Clean Pasture	6.71	6.79	6.90
06	Shrubby pasture	Dirty Pasture	1.26	1.12	1.01
07	Regeneration with Pasture	Dirty Pasture	0.96	1.26	0.93
08	Pasture with exposed soil	Dirty Pasture	0.012	0.007	0.001
09	Secondary Vegetation	Secondary Veget.	3.02	3.30	3.45
10	Others	Other	0.010	0.055	0.122
11	Non-observed area	(Discarded)	0.91	0.91	1.38
12	Reforestation	Other	0.0	0.060	0.063
13	No forest (cerrado biome)	(Discarded)	19.06	19.01	19.01
14	Primary forest	Forest	64.25	63.80	63.61
15	Hydrography (rivers/lakes)	(Discarded)	2.29	2.30	2.30
16	Recently deforested areas	Forest	0.23	0.13	0.09

Table 3.1 shows the relative shares of the different land-cover classes for the three different years, indicating the overall changes. The class “herbaceous pasture”, which has the biggest share in the productive land-use classes, increased, while shrubby pasture continuously decreased and pasture with regenerating vegetation first increased and then decreased again. All in all, the forest decreased more than the changes in pasture would sum up to, which is mostly due to the increase in secondary vegetation. There were also increases in land uses for annual crops, urban area, mining, and reforestation, but these classes make up only a very small fraction of the entire region. Finally, the areas that could not be observed, mostly due to cloud cover, show some variation between the different maps.

The numbers obtained from the data for this table are in line with the description by Almeida et al. (2016) for the 2008 map, who found that the dominant land cover on previously deforested land is pasture (62%), followed by secondary vegetation (21%). Annual crops only covered about 5% of the total deforested areas. These numbers only show the aggregate changes in the respective classes and do not provide insights neither into the spatial patterns nor the typical dynamics of the underlying land-cover changes. To find out more about these properties will be the main point of the following sections.

This chapter focuses on relevant transitions between major land-cover classes

occurring in different subregions of the Brazilian Amazon. Therefore, I first exclude patches from the analysis that could not be classified, for example due to cloud cover. Second, I discard land-cover types that do not change by definition, i. e., lakes and rivers and patches not belonging to the rainforest biome. Third, similar land-cover types are aggregated into six new classes. These classes combine different types of less intensively used pasture as well as types that only make up small fractions of the Amazon like mining and urban patches (see Table 3.1) and group land-cover types between which high confusion errors exist, thus decreasing them. In a final step of the data preparation, I assign patches to N different subregions. Depending on the scale of spatial aggregation of the analysis, the subregions either correspond to the legal municipalities of the Brazilian Amazon ($N=770$, as of 2007) or to the mesoregions ($N = 30$) as defined by the Instituto Brasileiro de Geografia e Estatística (Brazilian Institute of Geography and Statistics, IBGE, 2016).

3.3. A method to explore patterns of land-cover transitions

The comparison of land-cover dynamics between different subregions of the Amazon proceeds in two steps: First, the area in a given region that undergoes a transition from one land-cover type to another between two reference years is calculated (including the lumping of several land-cover types into one class, see Table 3.1) and the obtained matrices are normalized. Second, the transition matrices between subregions are compared by means of a cluster analysis and network methods. Before I describe the steps of the method in detail, I will give a short introduction to the theory of Markov chains.

3.3.1. Markov-chain theory

Markov chains are a main tool in many fields from computer linguistics to statistical physics. They have been described in many detailed publications (e. g., Revuz, 1984; Norris, 1997; Schinazi, 1999; Häggström, 2002; Modica and Poggiolini, 2013). Here, I recapture some basic properties of Markov chains. In general, Markov chains can be infinite, show periodicity or be continuous in time. Prominent examples for such chains are for example random walks in discrete space or birth-death processes. However, we are interested here only in discrete-time, finite, and homogeneous Markov chains.

A discrete-time finite Markov chain is a stochastic process X_t in discrete state space $S = \{s_i\}$, $i \in 1, \dots, N$, represented by transition probabilities $Pr(X_{t+1} = s_j | X_t = s_i)$ for going in one time step from a state s_i to a state s_j . If the transition probabilities are independent of the index of the chain (here time t), the process is called homogeneous. The transition probabilities of a homogeneous process can be summarized in a

transition matrix (stochastic matrix) $p_{ij} = Pr(X_{t+1} = s_j | X_t = s_i)$ with the following properties:

$$\forall i, j : p_{ij} \geq 0 \quad \text{and} \quad \forall j : \sum_{i=0}^N p_{ij} = 1. \quad (3.1)$$

Using this notation, the time evolution of a probability distribution over states $x_t \in \mathbb{R}^N$ is given by

$$x_{t+1} = \mathbf{p} x_t, \quad (3.2)$$

which implies that

$$x_t = \mathbf{p}^t x_0 \quad (3.3)$$

for some initial distribution of states x_0 . Many authors alternatively use a notation, where the rows of \mathbf{p} sum to 1, and the time evolution is given by multiplication of the vector from the left ($x_0 \mathbf{p}^t$).

The stochastic process described by the transition matrix is Markovian, which means that its future state only depends on the present state and not on the history of the process. Formally, this statement can be written as

$$Pr(X_{t+1} = s_{t+1} | X_t = s_t, X_{t-1} = s_{t-1}, \dots, X_0 = s_0) = Pr(X_{t+1} = s_{t+1} | X_t = s_t), \quad (3.4)$$

for all possible choices of the different s_t in S . Markov chains can also be represented by a weighted directed graph with weights p_{ij} on edges e_{ij} between the nodes representing the states of the Markov chain s_i (cp. Fig. 3.3).

Markov chains can have stationary distributions π , which are fixed points of the map $p(x) = \mathbf{p}x$ given by the stochastic matrix (Schinazi, 1999). A stationary distribution is a normalized eigenvector of the stochastic matrix corresponding to the eigenvalue $\lambda = 1$. This is the case because it is the solution of the defining equation for an eigenvector with eigenvalue 1,

$$\mathbf{p} \pi = \pi. \quad (3.5)$$

If the eigenspace of eigenvalue $\lambda = 1$ is one-dimensional, the stationary distribution is unique and any distribution of initial states will converge to it in the long run. The type of Markov chains analyzed in this section has a unique stationary distribution.

Another important concept of Markov-chain analysis are communicating classes. These are maximal sets of states in S that are all mutually accessible, i.e., that have a non-zero probability of being reached after some time again. More precisely, a state j is accessible from state i , if there exists a finite integer t_{ij} such that $Pr(X_{t_{ij}} = j | X_0 = i) > 0$. In the present application, not all states of the Markov chain form a communicating class, but those states not being part of the communicating

3.3. A method to explore patterns of land-cover transitions

class make only transitions to the single communicating class of the chain (for example the ‘Forest’ class).

The idea of Markov chains (without memory) can be extended to a Markov-type stochastic process with some memory. These so-called higher order Markov-chains are described by transition probabilities depending on a finite number of previous states. In the simplest case, the transition probability depends on the two previous states and can be described by a three dimensional array

$$p_{ijk} = Pr(X_{t+1} = s_k | X_t = s_j, X_{t-1} = s_k). \quad (3.6)$$

The state of such a system is described by a joint probability distribution of being at time t in state j and at time $t - 1$ in state k , $x_{jk} \in \mathbb{R}^{N \times N}$. The dynamics of such a distribution is then described by the following equation:

$$x_{ij}^{t+1} = \sum_k p_{ijk} x_{jk}^t. \quad (3.7)$$

A second-order Markov chain is not Markovian in the strict sense but it can be mapped to a first-order Markov chain with a state space of dimension N^2 .

In the following, I will show how the transition matrices of Markov chains that represent land patches undergoing transitions between different land-cover types can be estimated from land-use change data.

3.3.2. Extraction and normalization of transition matrices

A subregion of the Amazon can be thought of as consisting of a number of land patches that undergo transitions between land-cover classes. Markov analysis then describes how the set of patches may change over time. Although the Markov property can be shown to hold approximately for land-use systems (Robinson, 1978), the transition rates are generally not constant over time, which means the system is not stationary. This is not surprising because of the various climatological and socioeconomic drivers and political decisions influencing land-cover dynamics (Walker, 2004). Even though Markov chain analysis may oversimplify land-cover dynamics because it does not take the underlying processes explicitly into account, it serves here as a first approximation in obtaining a general understanding of the land-cover dynamics observed in the data.

The transition matrices of subregions are obtained by calculating the areas in a given subregion that undergo a transition from a land-cover class i to another class j . The transition matrix of one subregion $\mathbf{T}(t)$ is an $n \times n$ matrix with elements $T_{ij}(t)$, $i, j \in \{1, \dots, n\}$, where n is the number of land-cover classes. The transition matrix depends on time, indicating the non-stationarity of the Markov process. In the following, however, I omit the time dependence for ease of notation. With the aggregation described in Table 3.1, $n = 6$. T_{ij} is estimated from the data by first projecting the coordinates of the patches (in the data given in the *South American Datum* (SAD69) coordinate system) to the *South America Albers Equal Area Conic* projection. Second, the geometric union is computed with a GIS software combining

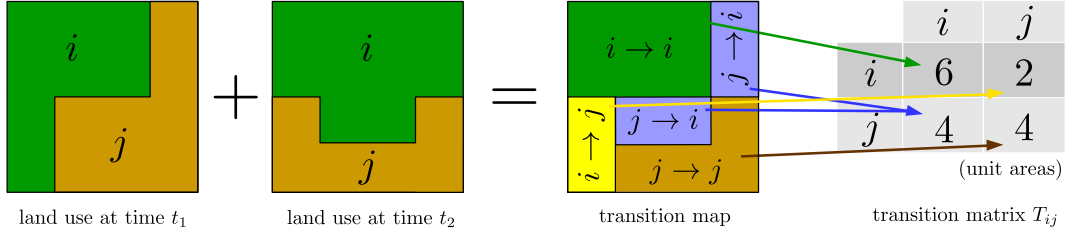


Figure 3.2.: Illustration of the geometric union operation that combines the information of two land-cover maps into a transition map and how the transition matrices are obtained from this map.

the information contained in the two land-cover maps of the reference years into one data set. Finally, the areas of all patches in one subregion that undergo the same transition are summed up. Figure 3.2 illustrates the creation of the transition matrix T_{ij} from the data.

To estimate transition probabilities, I normalize the transition matrices. This also makes subregions of different total area comparable. The normalization of the rows of the transition matrices to 1 allows to focus on relative changes in single land-cover classes,

$$p_{ij} = \frac{T_{ij}}{\sum_k T_{ik}} \text{ for } i, j : 1 \dots n. \quad (3.8)$$

The normalization does not work if one land-cover class i does not appear in the data of a subregion because $\sum_k T_{ik}$ would then be equal to zero. In such cases, the diagonal element is set to $T_{ii} = 1$, assuming that the land-cover class in the particular subregion does not undergo any changes.

As explained in Sect. 3.3.1, $\mathbf{p} = (p_{ij})$ can be interpreted as a stochastic matrix. It corresponds to the maximum likelihood estimation of the transition probability matrix of a first order Markov chain where land-cover classes correspond to the states of the Markov chain and the rows of \mathbf{p} specify the transition probabilities between the states (Anderson and Goodman, 1957).

Table 3.2 displays a Markov transition matrix for the Brazilian Amazon estimated from the land-cover transition between 2010 and 2012. The corresponding Markov chain is presented in Fig. 3.3(a). It shows that there are transitions between almost all aggregated classes, but they occur with very different probabilities. After deforestation, about two thirds of the areas are used as pasture, whereas the rest is mostly classified as secondary vegetation. Furthermore, transitions occur frequently between pasture partly covered with woody vegetation (dirty pasture) and clean pasture. The former makes also frequent transitions to secondary vegetation. Finally, there are considerable transitions from and to the “other” class, in which the minor land-cover types “mosaic of uses”, “urban area”, “mining”, “other” and “reforestation” from the original TerraClass classification are put together.

3.3. A method to explore patterns of land-cover transitions

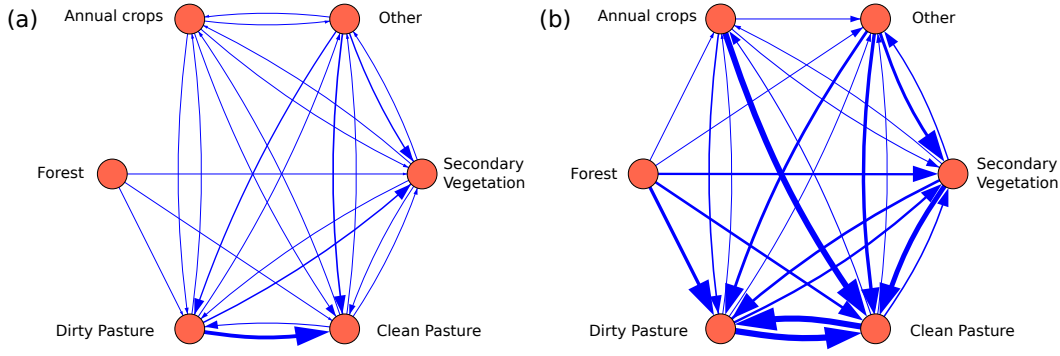


Figure 3.3.: Illustration of the normalized transition matrices between simplified classes derived for the whole Brazilian Amazon from the TerraClass data set (changes between 2010 and 2012): (a) Markov transition matrix \mathbf{p} (self-loops omitted) (b) conditional transition matrix \mathbf{q} . The strengths of the arrows are scaled with the transition probabilities except for those representing small values. Arrows with very small values (below 0.005) are not shown. The values are given in Tables 3.2 and 3.3.

Table 3.2.: Markov transition matrix \mathbf{p} for the Brazilian Amazon from 2010 to 2012 as depicted in Fig. 3(a). If the rows do not sum up exactly to 1, this is due to rounding.

TC2012	Secondary Vegetation	Clean Pasture	Dirty Pasture	Forest	Annual Crops	Other
TC2010						
Secondary Vegetation	0.87	0.07	0.037	0	0.0038	0.019
Clean Pasture	0.026	0.84	0.11	0	0.018	0.009
Dirty Pasture	0.16	0.42	0.39	0	0.0066	0.03
Forest	0.0008	0.00091	0.0012	0.9987	0.00006	0.00031
Annual Crops	0.016	0.098	0.025	0	0.85	0.011
Other	0.15	0.17	0.14	0	0	0.54

Alternatively to the Markov analysis, one could normalize the sum of the transition matrix elements T_{ij} to one. Such a normalization keeps the information on the initial distribution of land-cover classes in one subregion but does not allow to analyze relative changes in individual land-cover classes.

The transition matrix \mathbf{p} , representing the dynamics of an underlying Markov chain process, includes information on the patches that undergo changes and the patches that remain in their land-cover class. To only consider changes, the diagonal elements are set to zero before normalizing the rows of \mathbf{T} to 1,

$$q_{ij} = \begin{cases} \frac{T_{ij}}{\sum_{k \neq i} T_{ik}} & \text{for } i \neq j \\ 0 & \text{for } i = j. \end{cases} \quad (3.9)$$

Table 3.3.: Conditional transition matrix \mathbf{q} for the Brazilian Amazon from 2010 to 2012 as depicted in Fig. 3(b).

TC ₂₀₁₂	Secondary Vegetation	Clean Pasture	Dirty Pasture	Forest	Annual Crops	Other
TC ₂₀₁₀						
Secondary Vegetation	-	0.54	0.28	0	0.029	0.15
Clean Pasture	0.16	-	0.67	0	0.11	0.056
Dirty Pasture	0.26	0.68	-	0	0.011	0.05
Forest	0.25	0.28	0.36	-	0.019	0.097
Annual Crops	0.1	0.66	0.17	0	-	0.071
Other	0.32	0.37	0.31	0	0	-

$\mathbf{q} = (q_{ij})$ thus estimates the probability to make a transition from a single land-cover class i conditional on that there is a transition to a different land-cover class j . Table 3.3 displays such a conditional transition matrix for the entire Brazilian Amazon (2010-2012). Figure 3.3(b) shows a visualization of these numbers. For land-cover classes that have a high proportion of patches remaining in the same class, this figure allows inspecting the relative shares of transitioning patches more easily.

The normalized matrices \mathbf{p} and \mathbf{q} describe the transitions between all land-cover classes. In the following, I focus on comparing transition probabilities from a single land-cover class to all others, formally represented by the rows of the normalized matrices. If only focusing on the rows, the above-mentioned problem of missing land-cover classes in a subregion can be solved by simply discarding the respective subregions from the analysis. To increase the robustness, I also discard subregions having less than 1 km² of the considered land-cover class. This is especially important for the estimation of the conditional transition matrices because otherwise the addition of a minimal transitioning area could have a strong influence on the results.

Using the method described above, I estimated the normalized transition matrices \mathbf{p} and \mathbf{q} for all mesoregions and municipalities separately. This spatial segmentation was chosen because it makes the analysis compatible with other data (e. g., socioeconomic data sets provided by the IBGE). Additionally, the size of the municipalities reflect to some degree that of the population and therefore potential land-use activities. In principle, a segmentation into regular grid cells could provide complementary information and insights. However, to keep the presentation clear, I focus here on mesoregions and municipalities.

In general, the lower the spatial aggregation, i. e., the smaller the size of the subregions, the higher is the variability in space and in time. In a comparison of the mesoregion and municipality maps and transitions between different times this can be observed. Figure 3.4 shows two exemplary components of the matrices \mathbf{q} calculated for each municipality. The two maps highlight subregions in darker colors in which the transition rate from clean pasture to secondary vegetation and vice versa is high compared to transitions to other land covers. In Fig. 3.4(a), we can observe that transitions from clean pasture to secondary vegetation are infrequent compared

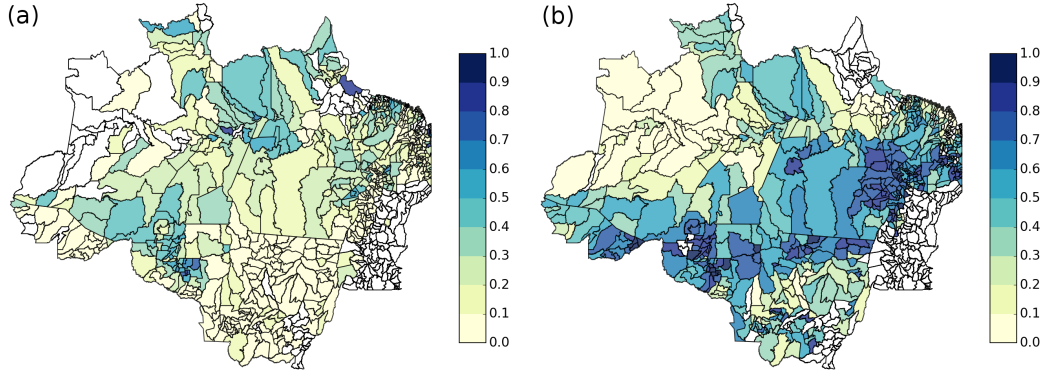


Figure 3.4.: Map of two selected components of the conditional transition matrices \mathbf{q} for each municipality of the Brazilian legal Amazon. Colors indicate the shares of areas that make a transition from (a) clean pasture to secondary vegetation and (b) secondary vegetation to clean pasture.

to other transitions except in the central North and the South West. Figure 3.4(b) suggests that along a horizontal band from the West to the East and in the North (state of Roraima) the transition rate from secondary vegetation to clean pasture is higher than in the other parts of the Brazilian Amazon. The maps in Fig. 3.4 and similar maps for all other possible transitions contain the information that that should be aggregated using clustering analysis. The next section therefore describes this second step of the presented method.

3.3.3. Construction of similarity networks and clustering analysis of land-cover transitions

Clustering methods are a basic technique to classify data points in a data set according to specific criteria and has been studied in the machine learning and data mining literature (e.g., Jain and Dubes, 1988; Gan, Ma, and Wu, 2007; Murphy, 2012). In recent years, the basic problem of clustering nodes in complex networks has also gained a lot of interest in complex systems science (Fortunato, 2010). For this study, I choose a combination of established and more recent clustering methods to compare and test the robustness of the obtained results. The chosen established methods are hierarchical clustering and the k-means algorithm. The other methods are based on complex networks constructed with a difference measure. To partition the network, I apply two different community detection algorithms, the fastgreedy and Louvain algorithms (Clauset, Newman, and Moore, 2004; Blondel et al., 2008).

The first method is hierarchical clustering, which merges data points or clusters based on their distance in the abstract data space. In the context of this analysis, a data point \vec{x} is either a full normalized transition matrix (flattened, such that $\vec{x} \in \mathbb{R}^{n^2}$) or a single row of such a matrix ($\vec{x} \in \mathbb{R}^n$). Each data point corresponds to

an individual subregion. To calculate the distance between two data points \vec{x} and \vec{y} , I use the ℓ_1 norm, also called Manhattan distance, $d(\vec{x}, \vec{y}) = ||x - y||_1 = \sum_i \text{abs}(x_i - y_i)$. This distance is easy to interpret in the context of probabilities: it is proportional to the probability from one probability distribution that has to be attributed differently to match another distribution. Compared to the euclidean metric, it does not punish outliers of a cluster that much. The distances between two clusters or one cluster and one data point are calculated using the complete linkage algorithm that takes the maximal distance between the data points of two clusters. The algorithm therefore identifies compact clusters with small diameters (Jain and Dubes, 1988). The result of hierarchical clustering is a dendrogram of cluster partitions, representing a hierarchy of clusters that are merged to higher-order clusters subsequently (see Fig. A.1). To obtain a specific number of clusters the dendrogram can be cut at a certain level. There also exist different methods to determine the optimal number of clusters taking different properties of the distribution of cluster distances into account (Jain and Dubes, 1988).

The second method applied in this study uses k-means clustering. K-means clustering partitions a data set into of the fixed number of k clusters. It associates data points to centroids such that the within-cluster sum of squared distances is minimized and therefore needs to use the euclidean distance for comparing data points. For a cluster C_k with n_k data points, the centroid is $\mu_k = 1/n_k \sum_{j \in C_k} x_j$. The sum of squared distances is then given by $E^2 = \sum_{C_k} \sum_{j \in C_k} |x_j - \mu_k|^2$, where $|\cdot|$ is the euclidian distance. There are different algorithms to solve this clustering problem. Here, an implementation of Lloyd's algorithm is used (Lloyd, 1982; Pedregosa et al., 2011). The algorithm solves the problem iteratively: It starts with an initial assignment of data points to clusters and then reassigns data points between the clusters if they improve E^2 . The algorithm stops when further reassignments do not improve the target function. Different initial assignments can help to verify that the reached optimum is not only a local but also the global one.

The network methods both require the construction of a similarity network first. In the network, each node v_α represents a subregion and nodes with similar dynamics are linked by an edge $e_{\alpha\beta}$, where the greek character indices refer to subregions. The connectivity of the network can also be represented by an adjacency matrix $\mathbf{A} = (A_{\alpha\beta})$. To determine the similarity, I chose a normalized version of the Manhattan distance as the difference measure $d(\vec{x}, \vec{y}) = \frac{1}{2k} \sum_i \text{abs}(x_i - y_i)$. In this formula, k is the number of land-cover classes n in the case of comparing whole transition matrices and $k = 1$ in the case of transition vectors from single land-cover classes. This metric is zero if and only if transition probabilities are equal and 1 if they are completely different. A threshold d_{th} is chosen to transform the data into a network with the adjacency matrix \mathbf{A} :

$$A_{\alpha\beta} = \begin{cases} 1 & \text{if } d(\vec{x}_\alpha, \vec{x}_\beta) < d_{th} \\ 0 & \text{else.} \end{cases} \quad (3.10)$$

This adjacency matrix contains all information on the similarity network. The

3.3. A method to explore patterns of land-cover transitions

threshold d_{th} is chosen such that only links that are significantly different from a distribution of difference measures of random vectors or matrices are realized. In order to obtain d_{th} , I use a Monte Carlo simulation to estimate a significance level: a large number (10^7) of random samples of vectors or flattened matrices $\vec{\xi}$ is generated by drawing values from a uniform distribution and normalizing them accordingly. By computing the differences $d_{rand,ij} = \|\vec{\xi}_i - \vec{\xi}_j\|_1$ in the sample, I can approximate the distribution by a histogram of the obtained difference values. From this distribution of pairwise difference measures $\rho(d_{rand})$, I use the 5th percentile to determine the threshold d_{th} . The distribution and choice of threshold for a vector with dimension 4 is illustrated in Fig. A.2.

A visualization of a similarity network is shown in Fig. 3.5 for transitions from clean pasture to other land-cover types. The nodes of the network represent data points for the municipality drawn around it. The network has links between regions with a difference measure below the significant threshold $d_{th} = 0.11$, which are obtained as described above from a Monte Carlo calculation of normalized random vectors of dimension 4 (because transitions to 4 other classes are possible). A visual inspection of the network suggests that similar transition probabilities are detected in regions of the Eastern and the Southern Amazon, whereas there are less similar transitions in the Northern part. The inset in Fig. 3.5 furthermore shows a histogram of all pairwise differences. The threshold is indicated as a red vertical line. From tests with different thresholds (i. e., percentiles of the distribution of differences) and different underlying data, I conclude that the patterns observed in the similarity networks hardly depend on the exact choice of the threshold (or link density). Thus the construction of the network is robust with respect to variations of the threshold.

The visual inspection of similarity networks is difficult and depends on the chosen visualization technique. Therefore, I used community detection algorithms to infer information about the underlying structure of the networks. These algorithms identify clusters of nodes on the network (in the literature the clusters are often called communities, hence the name) that have a high internal connectivity. Most of these algorithms are based on the idea of optimizing modularity Q , a network measure that compares the frequency of links inside of communities to the frequency of links inside the same communities of a network in which the degree of nodes is the same and the links are randomly and uniformly distributed (Fortunato, 2010). For a network with adjacency matrix \mathbf{A} and clusters C , the modularity is given by

$$Q = \frac{1}{2m} \sum_{\alpha, \beta} \left(A_{\alpha\beta} - \frac{k_{\alpha}k_{\beta}}{2m} \right) \delta(C_{\alpha}, C_{\beta}), \quad (3.11)$$

where $k_{\alpha} = \sum_{\beta} A_{\alpha\beta}$ is the degree of node α and m is the number of edges in the network. The term $\delta(C_{\alpha}, C_{\beta})$ only gives a contribution if nodes α and β belong to the same cluster. In the following, I apply the fastgreedy and the Louvain algorithms to the networks, because they are computationally efficient and yield comparatively high modularity values. The general idea of the fastgreedy algorithm as described in Clauset, Newman, and Moore (2004) is to subsequently join clusters such that

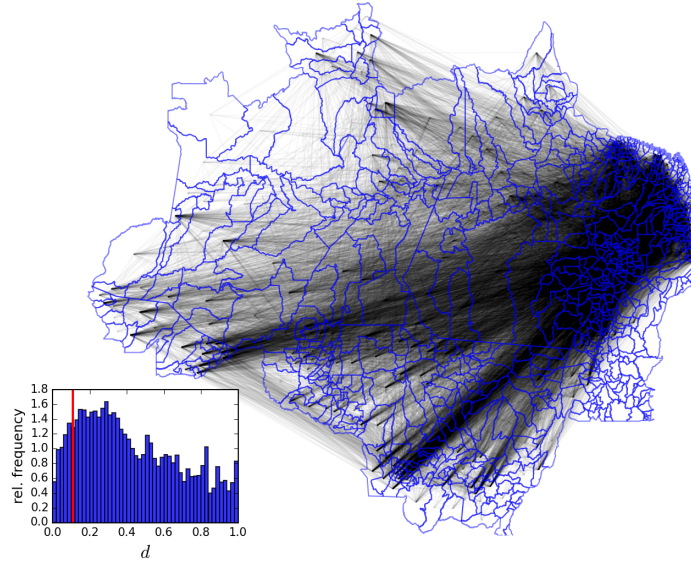


Figure 3.5.: Illustration of a similarity network with a spatial division in municipalities for transitions from clean pasture to other land-cover classes between 2010 and 2012. Inset: Histogram of difference metric values with threshold in red.

the increase in modularity is highest after the join. This produces a dendrogram, similar to the output of the hierarchical clustering method, which can be cut at the level of highest modularity Q . In contrast, the Louvain algorithm developed in Blondel et al. (2008) proceeds in two iterative steps: It first checks subsequently if the reassignment of single nodes to other clusters leads to an improvement in modularity. In a second step, it builds a new network combining all nodes of a community found in the previous step into one node and sums up all edges between communities to form weighted new edges.

In the following, I apply these algorithms to the same heterogeneous data. A comparison between the different methods will show whether the clustering can be considered robust.

3.4. Spatial heterogeneity of land-cover transitions and discussion of clustering patterns

This section describes patterns of land-cover change found in the Brazilian Amazon when applying the clustering algorithms of differently normalized transition matrices or single rows of them. I present the spatial comparison of transitions between 2010 and 2012 with the threshold for the construction of the similarity networks set to $d_{th} = 0.11$ (see Section 3.3.3). Comparisons of transitions between other years are shown in the appendix (Fig. A.6).

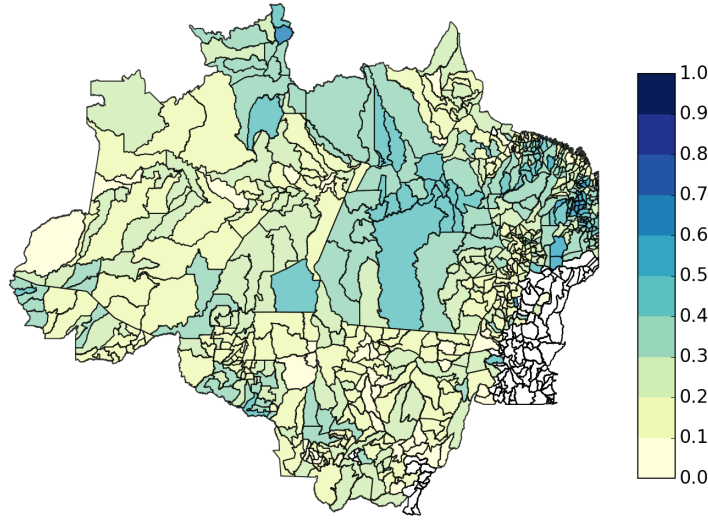


Figure 3.6.: Relative areas that undergo changes in land-use classes between the years 2010 and 2012 (excluding primary forest).

As explained before, there are different possibilities to normalize the transition matrices: the Markov matrices \mathbf{p} that also contain information about patches remaining in the same land-cover class and the conditional transition matrices \mathbf{q} that disregard this information. First, the analysis showed that the majority of land patches does not change its class from one time step to the next. This is illustrated in Fig. 3.6, where the relative area of patches that make a transition to a different land-cover class is plotted (excluding primary forest), i.e., the sum of the diagonal elements of the transition matrix divided by the sum of all elements. Only in the Central Amazon and in some of the smaller municipalities there are considerable fractions of up to 50% of the area undergoing a change in land-cover class. Because the main interest of this study is on the changes in land cover, I will focus the following discussion first on the conditional transitions matrices \mathbf{q} and compare only single rows between the municipalities, pointing out exemplary and interesting findings from the comprehensive analysis of different combinations of land-cover classes.

Fig. 3.7 displays the result of the clustering analysis for transitions from clean pasture to other land-cover classes. To make the clustering comparable, the number of clusters for the hierarchical and k-means clustering was adapted to the one obtained from the fastgreedy network clustering algorithm. As we can see in the figure, there are clearly distinguishable clusters in the South and the North West of the Amazon colored in orange and cyan for all four different clustering algorithms. These clusters are identified independently of the chosen clustering algorithm. In the other parts of the Amazon region, the clusters vary dependent on the applied clustering algorithm. Both network community detection algorithms identify similar clusters,

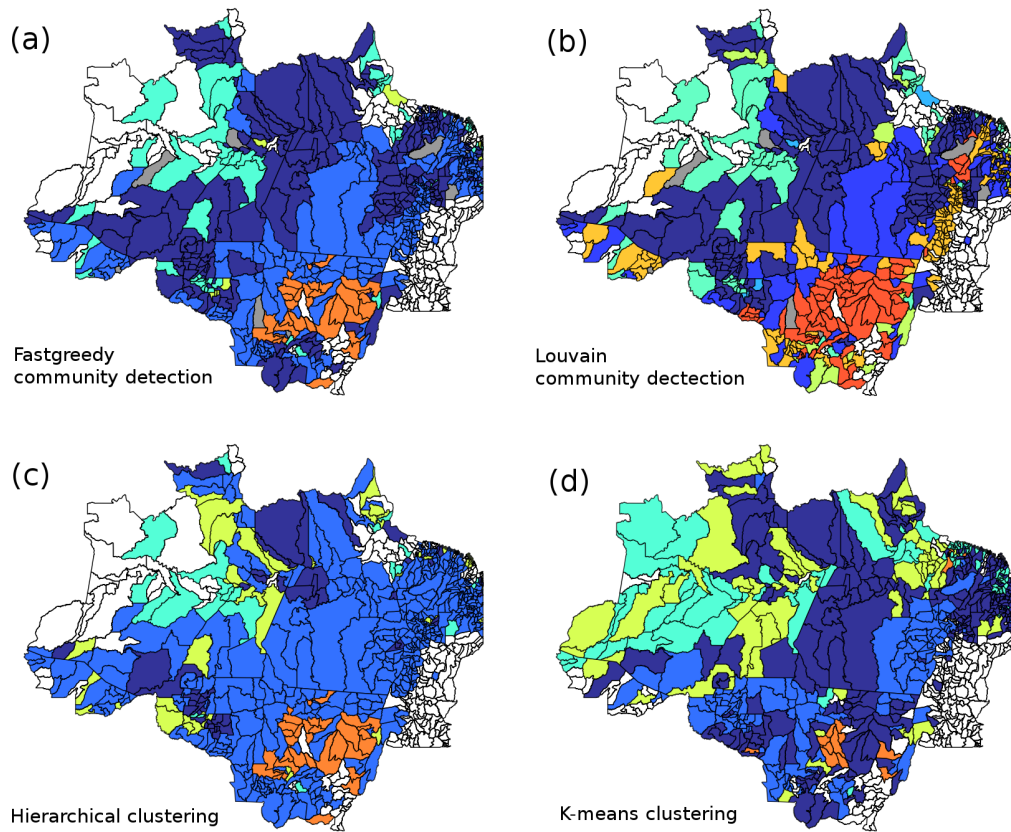


Figure 3.7.: Comparison of network (a, b) and classical (c, d) clustering algorithms for conditional transitions from clean pasture to other land-cover classes between 2010 and 2012. Each cluster is visualized by one color. White regions lack data to estimate the transition matrix, grey regions are not connected to the similarity network. The number of clusters for the hierarchical and k-means clusters was chosen to match the outcome of the fastgreedy algorithm (5). The Louvain algorithm detects 7 clusters.

even though the Louvain algorithm finds seven and the fastgreedy algorithm reveals five communities in the data. Also, some clustering algorithms seem to find two clusters for a group of municipalities, where other algorithms only find one (compare e.g., the fastgreedy with the k-means algorithm). In addition to the two relatively stable clusters, Fig. 3.7 shows that most clusters consist of adjacent municipalities. This suggests that neighboring municipalities have a high likelihood to exhibit similar relative land-cover changes.

To interpret the different clusters, I analyzed the cluster centroids, i.e., the mean of all data points in a cluster weighted by the area of the considered land patches in the subregion. Figure 3.8 shows the centroids of clusters obtained with the hierarchical

3.4. Heterogeneity of land-cover transitions and clustering patterns

clustering algorithm. The bars indicate the shares of patches making a transition from clean pasture to another land-cover class and thus show which transitions are dominating or are absent in the respective cluster. They allow a straight-forward interpretation of different clusters: For instance, in municipalities belonging to the orange cluster, most of the areas are converted to annual crops while only a small fraction makes the transition to dirty pasture. This is in line with a previous study by Macedo et al. (2012) who found that cropland in the Brazilian Amazon expanded mostly into pasture. The orange cluster is located inside the Mato Grosso State, one of the biggest producers of soybeans in Brazil. Soy beans are detected as annual crops in the data, which makes the concentration of this type of land-use transition in this particular area understandable. As we can see, the clusters generally differ by their relative shares of land-cover types such as dirty pasture and secondary vegetation. When comparing the cluster centroids between algorithms, these shares differ for the unstable clusters while the cluster centroids of the stable clusters are almost the same. This underlines the conjecture that some clusters actually represent some qualitatively different land-cover dynamics while others rather represent land-cover transitions that differ only quantitatively.

So far, I discussed transitions from clean pasture to other land-cover classes as one example. But the analysis has shown that the stable clusters identified in Fig. 3.8 can also be found when considering transitions from other land-cover classes, e. g., from secondary vegetation (see Figs. A.3 and A.4 in the appendix). However, the same patterns are not found for all transitions from single land-cover types. This is not surprising considering typical land-cover sequences (often called land-use trajectories) that follow total deforestation and that are discussed in the literature (Ramankutty et al., 2007; Alves et al., 2009; Espindola et al., 2012). According to these studies, a common land-cover trajectory begins with cleared forest patches that are converted to pasture land or used for small-scale subsistence agriculture. After a while, as the soil degrades, the areas are often abandoned leaving them for regrowth of secondary vegetation. Later, they may be cleared again and reused as pasture. This periodic use of land intermitted by fallow periods of secondary vegetation regrowth is an important mechanism determining for example greenhouse gas emissions in the region (Aguiar et al., 2016). Finally, areas may be converted to more intensive agricultural cropland, e. g., for soy bean cultivation or plantations. These accounts are generally consistent with the presented results.

In addition to the clustering based on transitions from single land-cover classes, the analysis aimed at identifying regions that are similar regarding the transitions between all land-cover classes. The clustering based on the full Markov matrices \mathbf{p} proved to be very unreliable due to the strong heterogeneity and dimensionality of the data. The different clustering algorithms yield quite different results, which can be interpreted as an indicator of missing robustness. The network community detection algorithms find partitions of the network with modularity values between 0.3 and 0.5. According to Clauset, Newman, and Moore (2004), this is a good indicator of a significant community structure in a network. The network algorithms are furthermore not sensitive to changes in link density of the similarity networks.

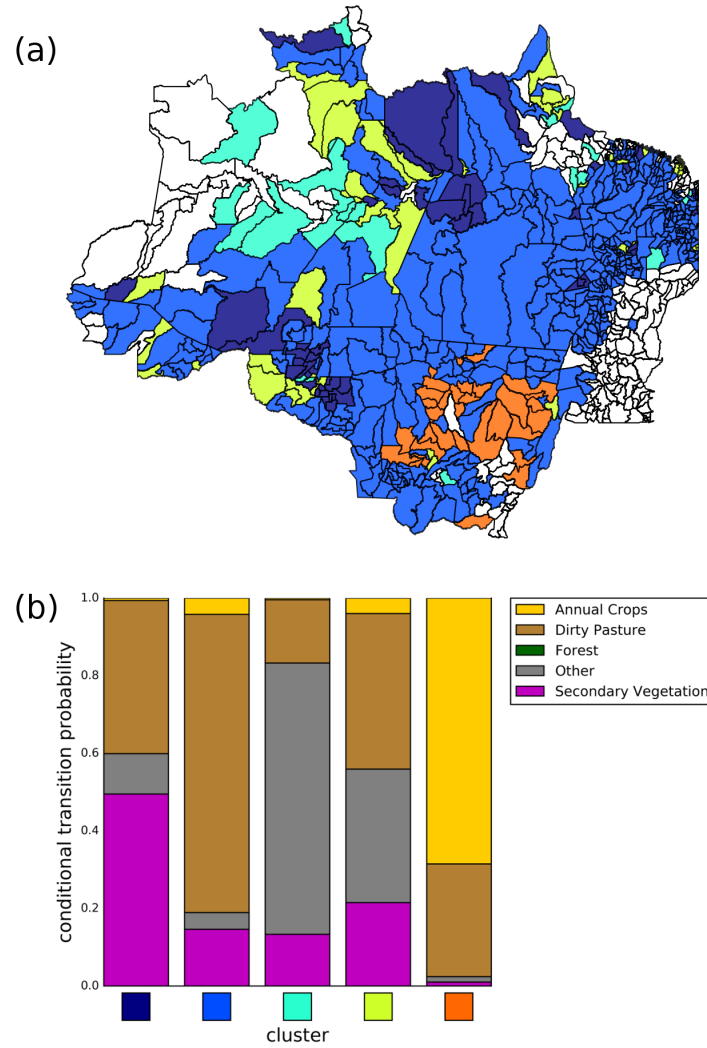


Figure 3.8.: (a) Hierarchical clustering with conditionally normalized transition probabilities from clean pasture to other land-cover classes between 2010 and 2012, as in Fig. 3.7(c). (b) Cluster centroids showing the conditional transition probabilities of the average over the respective cluster indicated by cluster color.

However, when comparing the results of different algorithms and with the classical clustering, there are significant differences (see Figs. A.5 and A.6). Furthermore, the analysis of the difference measure showed that only a small fraction of municipalities are significantly similar to each other compared to random matrices. The clustering based on the full conditional transition matrix \mathbf{q} turned out to be highly dependent on the assumptions made to fill in missing data. Thus, the analysis suggests that that a general classification of land-cover dynamics only based on the full transition

matrices between different land-cover types is not reliable.

This may have several reasons: First, the underlying processes of land-cover change in the Amazon are very heterogeneous in space and time and are therefore difficult to compare. For example, important processes like forest degradation through selective logging are not captured in the data set even though they have a huge influence on conversion to other land uses later. Second, the areas of the municipalities may be too small for a reliable estimation of transition probabilities. For this reason I also analyzed the transition matrices at the level of mesoregions (see Fig. A.7). However, there was no reliable clustering at this spatial aggregation either. Third, the classification of land-cover types in the TerraClass data set comes with considerable errors. The aggregation of some of the original classes already contributed to reducing these errors, because false classifications between aggregated land-cover classes are not relevant anymore. There is not yet an evaluation of the performance of change detection available for this data set, which makes an estimation of the errors in this analysis difficult.

Considering the negative results above, this study suggests that there are no overall clear patterns of land-cover change in the Amazon, at least not in the estimated transition probabilities. The studies dividing the Amazon into remote, frontier and consolidated areas mentioned in the introduction of this chapter (Sect. 3.1) are based on observations and data from the 1990s and included information about the socioeconomic development in the region. Hence, there are two possibilities to reconcile the result of this study with this literature: First, it could be that there is no direct link between the socioeconomic partitions of the region and the relative transitions in land-cover analyzed in this study. However, because the economic development in the region is still largely connected to agricultural development, the assumption that such a link does not exist is not plausible. Second, the large-scale socioeconomic patterns may have changed since the 1990 in such a way that the clear-cut distinction as proposed by Becker (2005) is not valid anymore. This hypothesis would need testing with other methods but could provide fruitful avenues for future research.

3.5. Projections with Markov-chain models

The transition matrices obtained in the previous analysis can be used to project the current land-cover change trends into the future, using the theory of Markov chains. This has been done in the literature (e. g., Bell and Hinojosa, 1977; Debussche et al., 1977; Aaviksoo, 1995; Luijten, 2003; Luo et al., 2008). For parts of the Amazon, Fearnside (1996) developed a Markov model to estimate greenhouse gas emissions from post-deforestation land use in the region.

In the following, I show how the transition probabilities estimated from land-cover data can be used to derive projections of land-use change for different land-use classes using first- and second-order Markov-chain models (see Sect. 3.3.1) and discuss the limitations of the presented models.

3.5.1. Results of Markov-chain projections

This subsection presents land-cover projections using the simplified land-cover classes given in Table 3.1. Projections with all TerraClass land-cover types can be found in the appendix (Figs. A.8 and A.9). Figure 3.9 shows projections with Markov transition probabilities derived for the entire Brazilian Amazon. For the first-order Markov-chain, the transition probabilities were obtained by normalization after averaging over the areas for the two available transitions (one of them being shown in Table 3.2). In Panel 3.9(a), I plot the development of the relative share of land-cover types starting with the distribution from the data in 2008 using Eq. 3.2. The projection with the first-order Markov-chain suggests that the shares of all the land-use classes and secondary vegetation increase while the share of forest decreases by about 23 percentage points of total area over a period of 100 years. To get the total area of the respective land-cover classes, the displayed values have to be multiplied by the absolute area of the whole region, which is about 3.8 million km², when disregarding areas that could not be classified in either of the analyzed years as well as water bodies and non-forest areas.

The calculation of the stationary distribution was obtained by normalizing the eigenvector of eigenvalue $\lambda_0 = 1$, as explained above. Figure 3.9(b) displays the values of the stationary distribution and illustrates how the shares converge to these values over time. Note, however, that the time scale for the convergence is very slow. This has to do with the comparatively low deforestation rates observed over the period 2008 to 2012 and their extremely strong extrapolation for this calculation.

For the second-order Markov chain, the transition probability array can be estimated using the data presented in the previous sections by summing the areas that were in a specific land-cover state at each of the three points in time, arranging them into a 3D-array with the states in different years as axes and normalizing the resulting array accordingly. Panels (c) and (d) in Fig. 3.9 show the resulting projections for the second-order Markov chain of land-cover transitions in the Brazilian Amazon using Eq. 3.7. This projection results in a slightly lower increase for example in secondary vegetation, but it does not show qualitatively different dynamics compared to the regular Markov chain.

The processes underlying the dominating transitions between the different land-cover classes are illustrated in Fig. 3.10. While the transition from forest to different pasture types and secondary vegetation is obviously deforestation, transitions between secondary vegetation and other land-use classes can be associated with land abandonment and reuse of previously deforested areas. Furthermore, there are different types of conversions taking place between pasture, annual crops and other land uses. Note that there may be more transitions occurring on the ground that are not captured in the data, because the maps represent the status of land cover with a sampling only every two years.

3.5. Projections with Markov-chain models

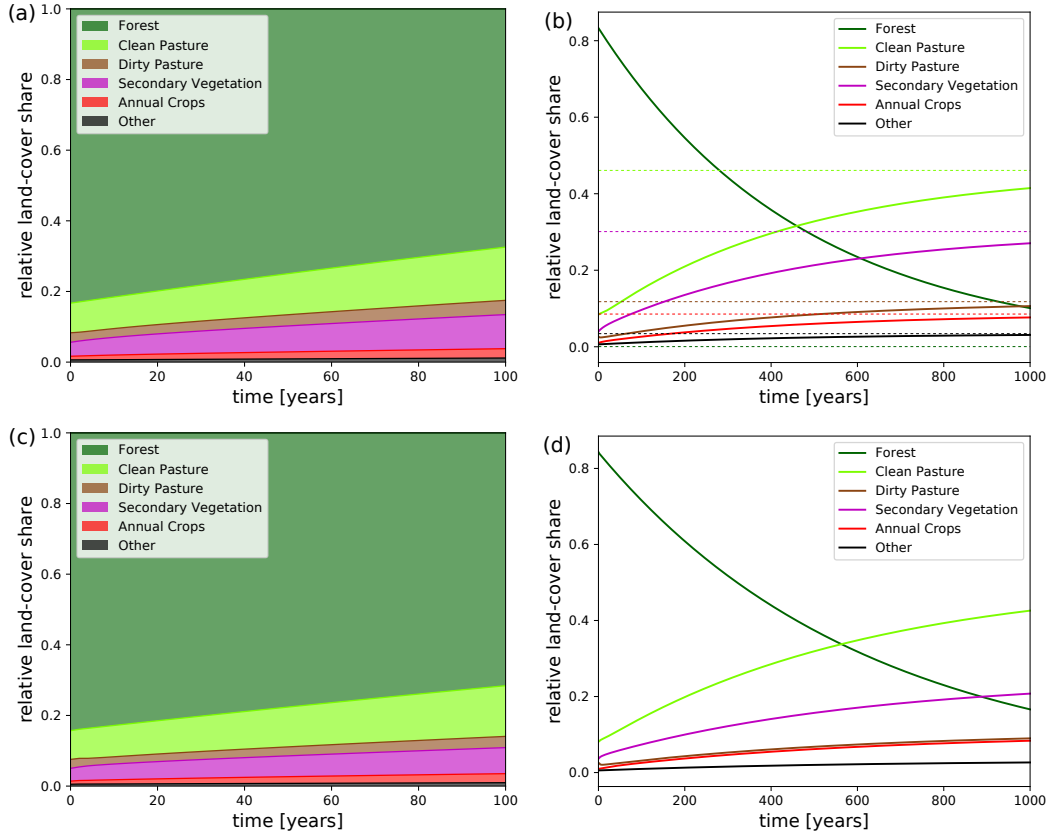


Figure 3.9.: Projections of land-cover dynamics modeled with two types of Markov-chains parameterized to the Brazilian Amazon: first-order Markov chain (a, b) and second-order Markov-chain (c, d). The stacked area plots (a, c) show the development of relative shares of land-cover types extrapolated for the next 100 years. The unstacked representation (b, d) with continuous lines representing the time evolution of relative shares was chosen to depict their convergence to the corresponding stationary values (dotted lines in b).

3.5.2. Discussion: limitations of Markov-type land-cover change models

The presented projections have important limitations because of the assumptions in the underlying Markov models. First, simple Markov models do not take spatial correlations into account. This is why they are often only one part of hybrid land-cover models (see e.g., Brown, Pijanowski, and Duh, 2000; Subedi, Subedi, and Thapa, 2013). The Markov submodules introduce stochasticity into such models, thus capturing changes that cannot be explained by other drivers in the model. However, they need to be complemented by mathematical structures that model spatial relationships. Many land-use models use cellular automata for this purpose

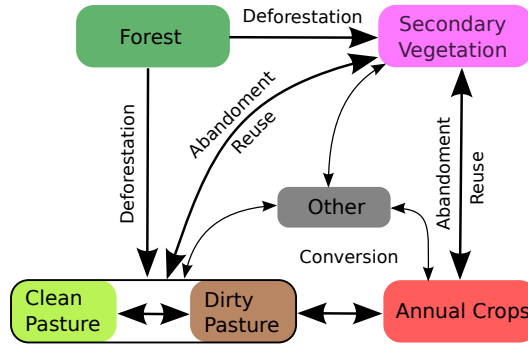


Figure 3.10.: Illustration of land-cover transitions in the Markov-chain models and interpretation of the underlying activities and processes of the transitions between land-cover types.

(see, e. g., White, Engelen, and Uljee, 1997; Marshall and Randhir, 2008; Chen, Yu, and Zhang, 2013; Yang, Zheng, and Chen, 2014). A cellular automaton is a system represented by an array of cells that have a specified state. The states make transitions depending on their previous state as well as on the state of their neighbors in the array (Wolfram, 1984). The resulting land-use models can be classified as stochastic cellular automata. Other extensions have been proposed to include non-exponential waiting time distributions between land-cover transitions (Moore, 1990). Such models can show very complex dynamics, which makes them difficult to analyze.

The second limitation is more severe: Markov-chain models, like any purely statistical model, do not take the dynamics of the underlying processes and drivers into account. This distinguishes them from so-called process-based approaches. They can only extrapolate past trends into the future without accounting for anticipated changes in the underlying drivers and their influence on the change processes. One way to partially overcome this limitation would be to investigate the dependency of transition probabilities on some of these drivers. This would need large data sets and is not possible when only land-cover maps of few time slices are available. However, even such an extension does not modify the conclusion that such models do not account for the underlying processes leading to land-use change. This is the reason why they are no adequate tool to help designing effective anti-deforestation policies.

In the following chapter, I present an agent-based model, which captures on the one hand agent decision-making in a stylized way and on the other hand includes a process-based description of how external drivers, e. g., in the form of price parameters, act on the system.

3.6. Summary

In this chapter, I have explored variations of methods from Markov and network analysis that are able to provide information on land-cover dynamics, including the

ability to quantify and compare land-cover transition frequencies, identify regions of similar patterns of land-cover change, and project currently observed transition patterns into the future. Clustering techniques were used to find patterns in subregional transition probabilities between land-use classes.

In the comparisons of transitions from single land-use classes, spatial patterns of relative land-use changes are consistent between different clustering methods and the detected patterns of subregions presenting similar transitions dynamics can be linked to insights from the literature. However, the analysis also indicates that relative land-use transitions between all land-use classes do not follow clearly distinguishable patterns that are related to earlier socioeconomic partitions of the Brazilian Amazon.

Furthermore, I showed how the results of the analysis can be used to parametrize Markov-type models of land-cover change that track aggregate areas with different land-cover types and project the observed transitions into the future.

The presented analysis is a first step toward an comprehensive analysis of regional land-use change dynamics using large-scale data sets. High quality data over longer time periods could improve the results of analyses such as the one presented here. With more data available, the proposed method could be extended for example by integrating socioeconomic data. This could potentially yield insights about the underlying drivers of land-cover transitions and how regionally different transition probabilities are determined. An integration of simple land-cover transition models with socioeconomic drivers could potentially overcome some of the discussed limitations of Markov approaches to land-use change modeling. However, I conclude that these methods do not adequately consider the role of agent decision making and therefore have only limited usefulness in guiding policy design.

Chapter 4.

Agent-based modeling of deforestation and cattle ranching in the Brazilian Amazon

4.1. Introduction

This chapter presents an agent-based model developed to investigate the following question: Can the intensification of cattle ranching lead to a decrease in deforestation in frontier regions of the Brazilian Amazon? Similar questions have been discussed in agricultural economics, mainly with respect to technologies that increase crop yields (e.g., Rudel et al., 2009, and references therein). A common rationale is the following: Low-intensity production technologies can lead to excessive use of land if it is easily available and accessible. Therefore, as yields per area increase, the area used for production of agricultural commodities will decrease, helping to ease pressure on ecologically valuable areas. This idea is often referred to as the Borlaug hypothesis (Angelsen and Kaimowitz, 2001, p.3).

The discussion about intensification and land sparing has mainly focused on crop production but it is also important for the livestock system. In the Amazon, the development of livestock production, especially beef cattle ranching, drives expansion of pastures into the rainforest (Barona et al., 2010; Pacheco and Poccard-Chapuis, 2012). While more than 60% of the deforested area in the Brazilian legal Amazon was used as pasture by 2008, only about 5% was used for crop production (Almeida et al., 2016). In the last decades, the opening of the region to national and international markets has led to a shift from extractive land-use activities to cattle ranching and increased the activities of agribusiness including the development of a supply chain for meat processing (Salisbury and Schmink, 2007; Pacheco and Poccard-Chapuis, 2012). This increased the demand for agricultural land in the Amazon basin considerably, also via indirect effects (Richards, Walker, and Arima, 2014). The expansion of pasture land leads to large-scale deforestation with strong adverse impacts on biodiversity and local climate. Reduced precipitation results from lower evapotranspiration from deforested areas (Zemp et al., 2017a). This in turn feeds back on agricultural productivity (Oliveira et al., 2013). The process may constitute a tipping element with relevance for global climate (Lenton et al., 2008).

On average, cattle ranching in the Amazon is characterized by extensive production systems with low stocking rates compared to other regions (the number of beef cattle per hectare is $0.4 - 1.3$, Pacheco and Poccard-Chapuis, 2012). Many extensive production techniques can be linked to environmental degradation in the region. Slash-and-burn methods are used to fertilize the land and may spark unintended forest fires (Cano-Crespo et al., 2015). In many areas, nutrient-poor soils lead to fast run-down of pasture fertility (Serrão et al., 1979; Myers and Robbins, 1991). Additionally, weed invasion, pests, compaction, and erosion further promote pasture run-down (Landers, 2007). The exhausted pastures are often abandoned and secondary vegetation starts to regrow on them (Perz and Skole, 2003b; Perz and Skole, 2003a). However, this forces the ranchers to replace them with pastures on newly deforested areas and move the frontier further into pristine forest.

Since the 2000s, there have been various efforts to reduce deforestation in the Brazilian Amazon (Nepstad et al., 2014). This includes the enforcement of environmental laws, which entails considerable costs and requires careful monitoring. As the stagnant deforestation rates show, the present policy measures have their limitations (Azevedo et al., 2017). For example, Richards et al. (2017) show that agents react to the current monitoring system by deforesting smaller patches to avoid detection. Besides, current environmental legislation, the so-called Forest Code, allows land-owners to deforest 20% of their private lands (Soares-Filho et al., 2014). Cutting only the legally available areas will already lead to large losses in biodiversity and considerable amounts of greenhouse gases released into the atmosphere (Aguilar et al., 2016).

For these reasons, policies that promote the intensification of cattle ranching have been suggested as a viable option to reduce deforestation (Cohn et al., 2014). Intensification could help ranchers use the already deforested land more efficiently and prevent them from deforesting more. These proposals are heavily criticized, arguing that higher profits from intensified land use may even increase deforestation rates (Angelsen and Kaimowitz, 1999; Kaimowitz and Angelsen, 2008). Other authors note that the success of intensification policies cannot be determined a priori but highly depends on the political, economic, and environmental circumstances (Latawiec et al., 2014).

Empirical evidence to support the effectiveness of intensification as a means to reduce deforestation in the Amazon is hard to assess. Cohn et al. (2011) review some of the cattle ranching intensification programs in Brazil that aim at the adoption of yield-increasing technology. They argue that due to a lack of data, the implementation of policies should proceed very carefully as it might result in unintended consequences. Soler, Verburg, and Alves (2014) find that land-use developments in the federal states of Mato Grosso and Rondônia are strongly linked to market accessibility and the land distribution structure. They cannot detect clear mechanisms that link land-use intensification to frontier expansion. Barretto et al. (2013) find that land-use intensification in frontier regions coincides with the expansion of agriculture. An analysis of deforestation drivers also shows that intensified land use is associated with higher incomes, which in turn can be linked to higher deforestation (Busch and

Ferretti-Gallon, 2017). After all, there are huge data gaps concerning the biomass flows through livestock systems (Erb et al., 2016), which makes the comparison of the effectiveness of different management techniques and technologies difficult. It is especially difficult to disentangle the effect of intensification from other influences and drivers (e.g., enforcement of legal protection) in empirical data. Another reason why an assessment of the impact of intensification policies remains an ongoing challenge is the huge heterogeneity of agents and their changing importance and roles in the deforestation process (Pacheco, 2012; Godar et al., 2014).

This chapter therefore investigates the interdependencies of intensification and deforestation using a theoretical modeling approach. Modeling has been used in the literature to investigate these interdependencies. For example, Bowman et al. (2012) use a spatial land rent model to find that intensification policies have to be complemented by improvements in conservation policies that discourage land speculation to decrease deforestation. Many land-use models apply a procedure that determines demands for different types of land and then allocates them geographically. They use economic criteria or empirically derived statistics describing the land-use potential and conversion elasticities of the modeled region to translate changing demands into changes in spatial land-use patterns (e.g., Verburg et al., 2002; Michetti, 2012; Aguiar et al., 2012).

To intensify their production, ranchers have to adopt new management practices and production technologies. Such decisions are not only based on economic considerations, but are also determined by the diffusion of knowledge and successful management practices via social networks (Feder and Umali, 1993). This has been demonstrated and modeled for example for the adoption of new agricultural technologies (Berger, 2001; Maertens and Barrett, 2012). Therefore, it is important to consider the social and cultural context of cattle ranching intensification to better understand its dynamics and impact on deforestation. For example, there are not only strong economic incentives but also cultural drivers, such as the dissemination and adoption of values connected to a cowboy culture, that make the current practice of cattle ranching attractive in comparison with more sustainable land uses (Hoelle, 2011).

Agent-based approaches can explicitly capture cultural influences and economic incentives on land-use change decisions of heterogeneous types of agents and are used to investigate how different drivers impact the deforestation dynamics. Section 2.6 provides a detailed review of agent-based models of social-ecological and land-use systems. Here, I want to highlight two agent-based models (ABMs) in the literature that explicitly focus on deforestation. Andersen et al. (2017) present a model of the households in a small Bolivian community and their decisions regarding land use (crop production and cattle ranching) and allocation of labor and capital. The households' decisions are modeled with utility maximization. The model is used to implement different policies, including the level of public investment, a deforestation tax, and conservation payments. However, the policies are not compared systematically.

The other notable example is an ABM of the Brazilian frontier region São Félix do Xingu designed to explore the role of institutional and political settings in frontier development in the recent decades (Costa, 2012). The model captures the influence of

different political settings on deforestation dynamics but does not explore the specific role of agents' decision making.

This chapter presents a stylized ABM to investigate under which circumstances intensification of cattle ranching can reduce deforestation in Amazon frontier regions. The model combines simplified representations of the social, economic, and ecological processes that are considered most important for the purpose of this study. It furthermore differs from the two above-mentioned ABMs by specifying heuristic land-management strategies and capturing how they change as a result of social influence. Such a combination of approaches has been identified as a promising representation of human decision making in social-ecological models (e.g., Müller-Hansen et al., 2017b).

The model is designed to explore the combined effect of dynamic processes and their emergent system-level outcomes, not to produce concrete numerical predictions or scenarios. To demonstrate the dynamics of the model, the model is parameterized and initialized with data from the frontier region around Novo Progresso in southern Pará, characterized by strong deforestation in recent years. The model design is scalable and can be adapted to other regions.

The remainder of the chapter is structured as follows: Section 4.2 describes the model set-up. The model results are analyzed in Sect. 4.3. Section 4.4 discusses the results and their implications for deforestation policies. Section 4.5 summarizes the chapter. The chapter is based on publication P4.

4.2. Model description

In this section, I describe the details of the agent-based model that is used throughout this chapter. The model describes a collection of N cattle ranchers (the agents) that interact with the local environment via decisions to convert forest into pasture land and manage this pasture. Deforestation and land abandonment is traced by simple land-cover succession equations. Ecological dynamics describe forest regrowth and the evolution of the productivity of pasture and secondary vegetation. The decisions of agents are represented by heuristic strategies depending on economic and ecological constraints. Agents can follow either an extensive strategy, corresponding to traditional cattle ranching with fallow periods and slash-and-burn fertilization, or a semi-intensive strategy, i.e., cattle ranching with inputs such as machinery and industrial fertilizers. The choice of the production strategy is modeled as a social learning process: Agents are located on a geographic network representing neighborhood and acquaintance relations and imitate the successful strategies of their neighbors. In the following, I describe these processes in detail. Table 4.1 gives an overview of the variables used for the formalization.

4.2.1. Ecological dynamics

Each agent i has a ranch with a constant area X that is covered by forest F_t , pasture P_t , and secondary vegetation S_t . In the following, I omit to mark all variables of

Table 4.1.: Overview of variables, symbols, and units in the agent-based model.

variable	symbol	unit
pasture area	P_t	ha
forest area	F_t	ha
secondary vegetation area	S_t	ha
pasture productivity	q_t	a.u.
secondary vegetation productivity	v_t	a.u.
savings of rancher	k_t	BRL
income	I_t	BRL
consumption	C_t	BRL
deforestation	d_t	ha/year
abandonment	a_t	ha/year
reuse	r_t	ha/year
management effort	m_t	a.u.
stocking rate for pasture	l_t	head/ha

single ranchers with an index i . Thus, $F_t + P_t + S_t = X$. This implies that there are two degrees of freedom in the dynamic variables that describe the different areas. The model is discrete in time t and each time step represents one year, thereby abstracting from seasonal variations. Land-cover changes such as deforestation and land abandonment are traced by simple land-cover succession equations (cp., e.g., Satake and Rudel, 2007). At each time step, pasture land can be created through deforestation d_t or reuse of land previously covered by secondary vegetation r_t . Pasture with area a_t can also be abandoned, leading to secondary vegetation regrowth. The change in pasture land is given by

$$P_{t+1} = P_t + d_t + r_t - a_t, \quad (4.1)$$

where d_t , r_t , and a_t are rates per year in units of area. The dynamics of forest and secondary vegetation are given by

$$F_{t+1} = F_t + r_n v_t S_t - d_t \quad \text{and} \quad (4.2)$$

$$S_{t+1} = X - P_{t+1} - F_{t+1} = S_t - r_n v_t S_t + a_t - r_t, \quad (4.3)$$

where r_n is a parameter that describes the natural recovery from secondary vegetation to mature forest proportional to the productivity of secondary vegetation v_t . The dynamic of v_t is explained below.

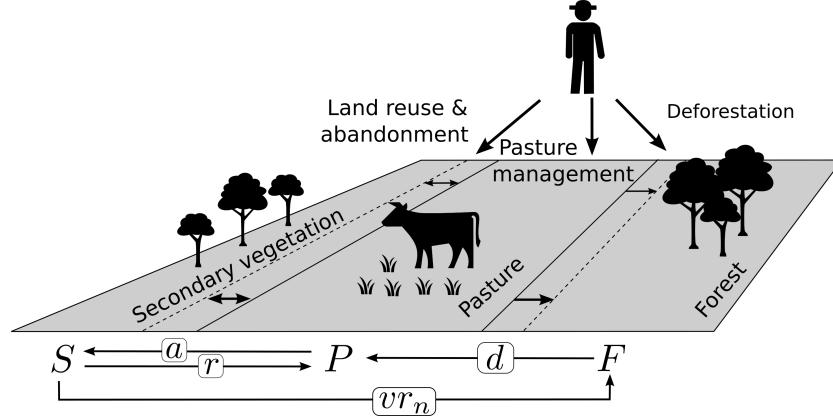


Figure 4.1.: Illustration of the conversion of land for single ranches in the model. The total area of a property is divided into three land-cover types that can be converted by land management with rates d (deforestation), a (abandonment), and r (reuse). Secondary vegetation regenerates with a rate proportional to a natural recovery parameter r_n and the productivity of secondary vegetation v . Cattle raised on the pasture generate revenues for the rancher.

The deforestation d_t , abandonment a_t , and reuse rates r_t are control variables chosen by the rancher and are determined as part of the decision process. The land-cover dynamics of a single ranch are illustrated in Fig. 4.1.

The pasture land is characterized by an average productivity q_t . The agent can decide how much cattle to place on the pasture. Pasture productivity is decreasing if the stocking rate $l_t = L_t/P_t$ is high, i.e., there is a high number of cattle L_t per area on the pasture. This approach was chosen because higher stocking rates are associated overgrazing leading to faster pasture degradation (Landers, 2007). The model formulation implicitly assumes that the herd size of ranchers is variable through acquisition and sale of calves and the ranchers adjust it to their requirements (cp. Quaas et al., 2007). The decay of pasture productivity can be reduced by a management effort m_t , which subsumes various processes like fertilization, adoption of new grass species, fencing, and maintenance work.

For describing the dynamics of the pasture productivity, the simplest decreasing dynamics with a lower zero bound was chosen, which is an exponential decay. This dynamic ensures that the averaging over different land areas with different initial productivities is valid.¹² Deforestation and reuse add land area to the pasture with

¹²Assume that each ranch consists of separate land patches indexed by j with pasture productivity q_t^j . Only this type of dynamic makes the averaging before applying the dynamic equivalent to averaging after applying the dynamic:

$$\langle q_{t+1}^j \rangle = \langle (1 - \beta l_t) q_t^j \rangle = (1 - \beta l_t) \langle q_t^j \rangle.$$

q_t describes this average and thus can account for different initial productivities of the underlying land patches.

productivities q_d and v_t , respectively. Furthermore, abandonment lets the pasture area shrink. Averaging over all these changes and weighting with the respective areas yields the following dynamic for pasture productivity:

$$q_{t+1} = \frac{(1 - \beta(l_t - m_t))q_t(P_t - a_t) + q_d d_t + v_t r_t}{P_t + d_t + r_t - a_t}, \quad (4.4)$$

where β is the rate of degradation, l_t is the stocking rate of the pasture, q_d is the pasture productivity after deforestation, and m_t is a management effort that can counteract pasture degradation.

To complete the ecological dynamics, the variable v_t tracks the productivity and regrowth on land areas with secondary vegetation. It follows a similar dynamic as the pasture productivity, but with an exponential approach to the natural relative productivity $v^* = 1$ with rate r_S . The other terms stem from weighting and averaging for additional and outgoing areas, similar to Eq. 4.4.

$$v_{t+1} = \frac{(v_t + r_S(1 - v_t))(S_t - r_t) + a_t q_t}{S_t - r_t + a_t}. \quad (4.5)$$

In summary, the ecological state of each ranch has four degrees of freedom (P_t , F_t , q_t , and v_t).

4.2.2. Economic dynamics

d_t , r_t , a_t , l_t and m_t constitute the control variables of the ecological dynamics, representing the possible decisions for the rancher. The management m_t , deforestation d_t , and reuse r_t are associated with a cost per area. The income of the agent is realized from selling cattle $y_t = l_t P_t q_t / T_p$, where p_c is the price per head and T_p is the average time that cattle have to spend on the pasture until they can be slaughtered. Thus the income of the agent is given by:

$$I_t = p_c l_t P_t q_t / T_p - c_D d_t - c_R r_t - c_m m_t P_t, \quad (4.6)$$

where c_D and c_R are the cost of deforestation and reuse (per area) and c_m the cost of management (per area and effort).

This income can either be consumed or saved by the ranch, resulting in the following dynamic for the accumulated savings:

$$k_{t+1} = (1 + \delta)k_t + I_t - C_t, \quad (4.7)$$

with an interest rate δ . The income spent for consumption C_t also represents a choice for agents and is therefore a control in the model. Note that the savings can also be negative, such that they effectively represent the debt of the rancher. For simplicity, I assume a fixed saving rate s , such that $C_t = (1 - s)I_t$.

4.2.3. Decision making of agents and production strategies

The decision-making functions of agents are the centerpiece of the model. They determine the control variables at every time step. Because the decision to deforest may depend on many factors such as location, available resources, weather, beliefs about future prices and policies, and the choices of other agents, it is especially challenging to capture the decision-making functions appropriately in a stylized model.

Here, I use a heuristic decision approach for modeling the decisions of the ranchers. Heuristics are rules of thumb, often formalized as decision trees, that help agents to choose actions leading to more desirable outcomes over less desirable ones using the (possibly incomplete) information available (for a detailed discussion of heuristics, see Sect. 2.3.2). Heuristics have been used to model land-use decision, for example in the model by Deadman et al. (2004), which analyses colonist household decisions in the Amazon.

Because of limited empirical data on actual decision processes in the system under consideration, some simplifying assumptions for the decision functions of agents had to be made. In the model, the determining element for the decision process of an agent is the production strategy that an agent adopts. A review of the literature (see for example Pacheco and Poccard-Chapuis, 2012, and references therein) in combination with expert consultations identified two idealized strategies, an extensive and a semi-intensive land management strategy, which correspond to typical individual land-use trajectories in the Amazon. The decisions to deforest, manage the pasture, or abandon parts of it as well as to decide for a stocking rate depend on the management strategy that the agent has adopted.

4.2.4. Extensive strategy

The extensive strategy represents traditional approaches to cattle ranching and is characterized by low stocking densities. The pasture productivity decreases over time and has to be renewed by fallow periods and slash-and-burn practices (Fearnside, Barbosa, and de Alencastro Graça, 2007).

The choice of control variables in the presented model follows simple threshold heuristics that can be written using the Heaviside function

$$\theta(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases} \quad (4.8)$$

as a compact notation.

The decisions to deforest or reuse (i.e., slash-and-burn) an area D or R are determined as follows. First, the respective savings for covering the conversion costs c_D or c_R have to be available. The conversion can only take place, if there is enough forest F_t or secondary vegetation S_t . For the extensive strategy, the managed pasture cannot exceed a fixed fraction p_{max} . Finally, the expected additional income $I_{exp}^d = p_{clt} D q_d / T_p$ (or $I_{exp}^r = p_{clt} R v_t / T_p$ for reuse) from the additional pasture is

compared to the cost. If the investment redeems itself within a time period T_{rec} , the investment is made. If both deforestation and reuse redeem themselves, then the option with the higher expected additional income is taken. With the notation of Heaviside functions, this can be written as

$$d_t = D \theta(k_t - c_D D) \theta(F_t - D) \theta(p_{max} X - P_t) \theta(I_{exp}^d T_{rec} - c_D D) \theta(I_{exp}^d - I_{exp}^r), \quad (4.9)$$

$$r_t = R \theta(k_t - c_R R) \theta(S_t - R) \theta(p_{max} X - P_t) \theta(I_{exp}^r T_{rec} - c_R R) \theta(I_{exp}^r - I_{exp}^d). \quad (4.10)$$

An area A of pasture land is abandoned if pasture productivity falls below a certain threshold $q_{\theta a}$:

$$a_t = A \theta(q_t - q_{\theta a}) \theta(P_t - A). \quad (4.11)$$

The extensive strategy does not use the pasture management option ($m_t = 0$) and the stocking rate is fixed at a low level $l_t = l_{ext}$. A sample trajectory for the dynamics of a single ranch with the extensive strategy is shown in Fig. 4.2. The strong oscillations in the trajectory result from the thresholds in the decision functions. The agent has to reinvest into deforestation and reuse of secondary vegetation to improve the pasture productivity every few years.

4.2.5. Semi-intensive strategy

The semi-intensive strategy, corresponding to cattle ranching with various industrial inputs and pasture improvement techniques, has higher stocking densities but also higher costs for inputs. Agents invest in inputs for pasture maintenance such as fertilizers and fencing for pasture rotation, but also in measures such as better adapted grass and cattle species, improved pasture seeding with legumes, or additional concentrated feed to improve pasture and livestock productivity (Landers, 2007; Latawiec et al., 2014).

The semi-intensive strategy is implemented in the following way: Deforestation D occurs if there is enough primary forest on the property left and the agent has sufficient savings to cover the deforestation cost. Furthermore, the agent decides whether the investment to be made can be regained within a certain time period T_{rec} , assuming that the economic circumstances remain constant. For this, the expected income $I_{exp}^d = p_c l_t D q_d / T_p - c_m m_t D$ from using a newly deforested area is compared to the deforestation cost. In the case of the semi-intensive strategy, the calculation of income takes the costs for pasture management into account. The decision for reusing an area R is made similarly. As for the extensive strategy, the decision between deforestation or reuse to get new pasture results from a comparison of the expected income increases of both options.

$$d_t = D \theta(k_t - c_D D) \theta(F_t - D) \theta(I_{exp}^d T_{rec} - c_D D) \theta(I_{exp}^d - I_{exp}^r), \quad (4.12)$$

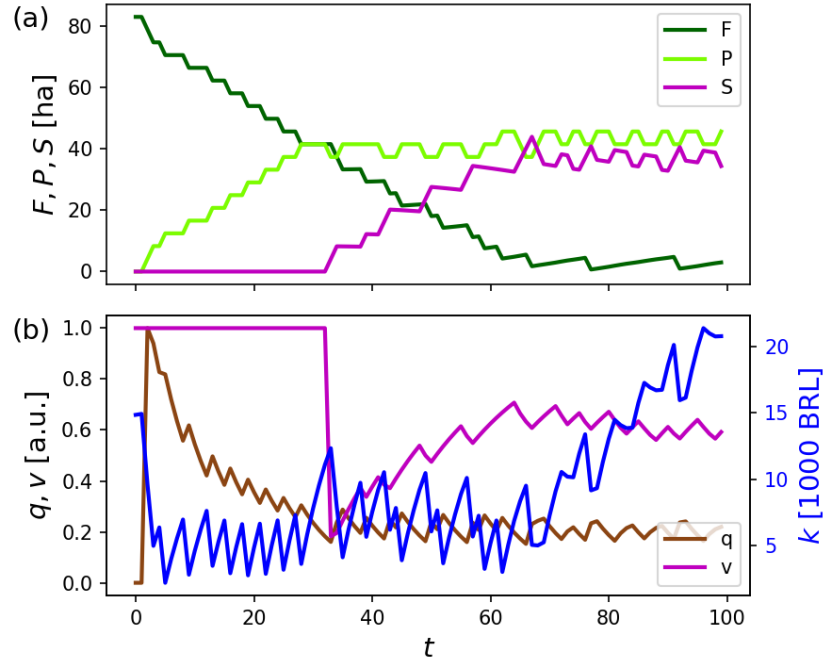


Figure 4.2.: Sample trajectory for illustration of the dynamics of a single ranch with extensive strategy, showing (a) the areas of different land use: pasture (light green), forest (dark green), and secondary vegetation (magenta) and (b) the pasture productivity (brown), secondary vegetation fertility (magenta), and savings (blue).

$$r_t = R \theta(k_t - c_R R) \theta(S_t - R) \theta(I_{exp}^r T_{rec} - c_R R) \theta(I_{exp}^r - I_{exp}^d). \quad (4.13)$$

An area A of pasture is abandoned if the ranching activity is not profitable anymore,

$$a_t = A \theta(-I_{exp}) \theta(P_t - A), \quad (4.14)$$

with $I_{exp} = p_c l_t P_t q_t / T_p - c_m m_t P_t$. The semi-intensive strategy uses the pasture management option $m_t = M$, where M is a constant. The stocking rate is higher than in the extensive case $l_t = l_{int} > l_{ext}$. A sample trajectory for this strategy is shown in Fig. 4.3. Here, one can observe that most of the forest is deforested quite fast and the decline of pasture productivity is much slower because of pasture management.

Evidence for the proposed kind of heuristic behavior was obtained in personal interviews by one of my co-authors (Eloi Dalla-Nora, unpublished fieldwork carried out in 2016 in the states of Pará and Mato Grosso along the highway BR-163). Ranchers tend to invest in new pasture if they can recover their initial investment in a time period below a threshold of about 5-8 years. Furthermore, the valuation of land is an important factor for decision making of ranchers. Because the model does

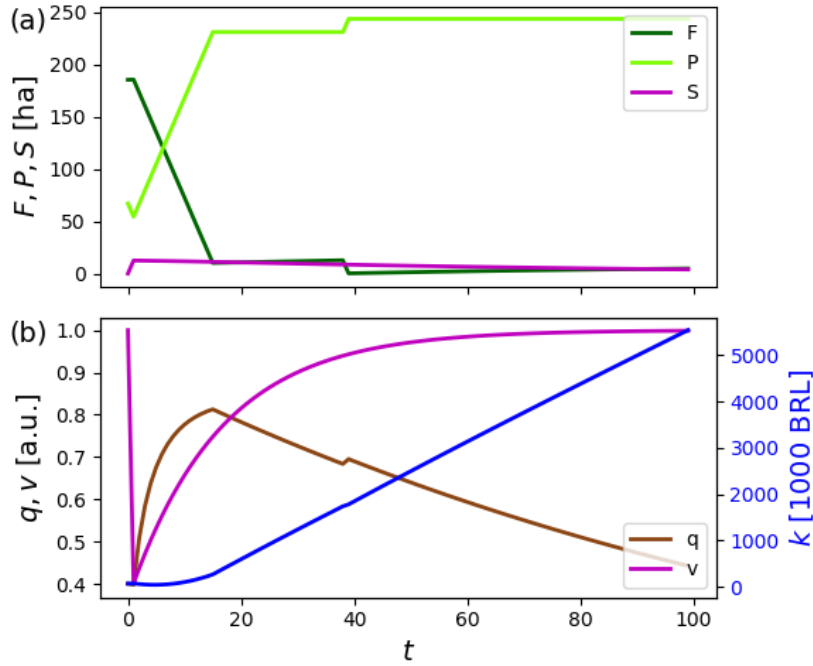


Figure 4.3.: Sample trajectory for illustration of the dynamics of a single ranch with the semi-intensive strategy: (a) areas of different land use: pasture (light green), forest (dark green), and secondary vegetation (magenta), (b) pasture productivity (brown), secondary vegetation fertility (magenta), and savings (blue).

not contain a description of the land market, this was not considered in the analysis.

4.2.6. Local interaction: strategy imitation between agents

The decision to adopt a certain production strategy could in principle take into account the amount of available land and savings, possibilities to move to other areas, and the available information about technologies and environmental factors. For the presented model, this potentially complex decision is reduced to a social imitation process on a geographic network, assuming that the adoption of a certain management strategy only depends on the agent's own success and its comparison with the neighbors (cp. Traulsen et al., 2010; Wiedermann et al., 2015).

The model describes the choice of management strategy as a social updating process: Strategies are transmitted via a network of neighbors and acquaintances (for a review of influence models and social networks see Sections 2.4.3 and 2.4.4). The agents are modeled on a network, which represents neighbor relations as illustrated in Fig. 4.4. This simplifying assumption is motivated by evidence from the literature that neighbor interactions play an important role in deforestation decisions (Robalino and Pfaff, 2012) and the role of social interactions on networks in various environmental

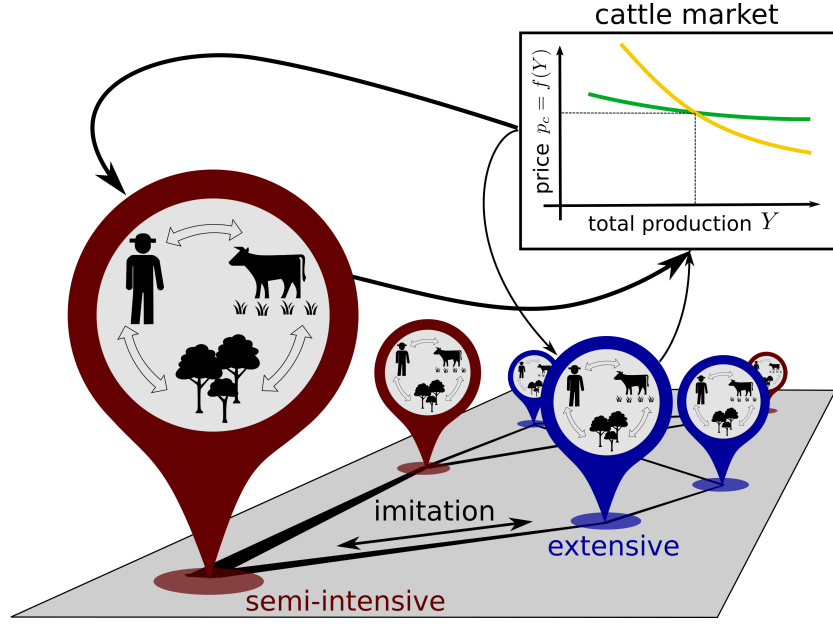


Figure 4.4.: Illustration of the local and system-wide interactions between agents: Agents can imitate their strategies (extensive, blue, or semi-intensive, red) if they are connected on a geographically embedded social network. They sell their cattle on a market that determines the cattle price and thus their income, depending on the price elasticity of demand (yellow curve: low price elasticity, green curve: high price elasticity).

contexts (Currarini, Marchiori, and Tavoni, 2016). Imitation of the intensive strategy is only possible if an intensification cost per area c_I can be afforded. This cost can also be paid by a credit (modeled as negative savings) up to a certain limit.

In the model, the neighbor interactions were implemented as follows: The simplest assumption for the timing of interaction events is that they are equally probable for every point in time. Such a stochastic process is called Poisson process and is described by a rate λ (Van Kampen, 2007). The number of interaction events K in one time step of the model (one year) is then given by a random number drawn from the Poisson distribution

$$P(K) = e^{-\lambda} \frac{\lambda^K}{K!}. \quad (4.15)$$

The number of interaction events for each time step in the model is therefore given by a random number drawn from this distribution. For each interaction event, a random node i of the network and a random neighbor j of this node are chosen. Then, i imitates the strategy of j with a probability given by

$$P_{ij} = g(x_i, x_j), \quad (4.16)$$

where x is a property of the agents and $g: \mathbb{R}^2 \rightarrow [0, 1]$. For the model implementation presented here, the consumption C_t of agents was chosen as the property for comparison and a hyperbolic tangent function was used to compute the probability because it has a sigmoidal increase and saturates for large differences (cp. Wiedermann et al., 2015):

$$P_{ij} = \frac{1}{2} (\tanh(\sigma(C_j - C_i)) + 1). \quad (4.17)$$

This strategy imitation results in the spread of production strategies biased towards the more income generating strategy.

4.2.7. Interaction between all agents: the cattle market

In addition to the local imitation, the model captures how ranchers interact on a local cattle market, which determines the price that ranchers can realize when selling their cattle. The cattle price is given by a demand curve that represents the local market for cattle. The price response to changes in cattle quantity $Y = \sum_i q_i P_i l_i$ is modeled by a constant elasticity function

$$p_c = a_p Y^{-1/\epsilon}, \quad (4.18)$$

with price elasticity of demand ϵ . This interaction is illustrated in the upper right of Fig. 4.4, where the yellow demand curve corresponds to a lower elasticity than the green one.

The exact curve is difficult to estimate from data, which is why I analyze the model for different settings of the price elasticity of demand and base prices (as given by the parameter a_p). However, there is a straight-forward interpretation of the elasticity: the price elasticity can be assumed to be lower and thus prices to be more sensitive to changes in quantity in regions with a market that is not well integrated into national or international markets.

4.2.8. Input data and parametrization

An estimation of the parameters of the model and their sources are given in Table 4.2. Some of the parameters cannot be determined from the data, especially those parameters regarding decision making. Therefore, I provide a detailed analysis of parameter dependency on model outcomes in the following section.

The model was run using the following input data for initial conditions and set-up. Initial values for pasture areas was approximated with deforestation data from PRODES (2018), using the data from 2000 as initial conditions. For comparison with other initial conditions, I also tested initial conditions corresponding to the deforestation extent in 2016. The initial conditions for secondary vegetation are set to zero. Initial values for the soil productivity q were randomly drawn from a uniform distribution of values between 0 and 1. Furthermore, initial savings drawn from a

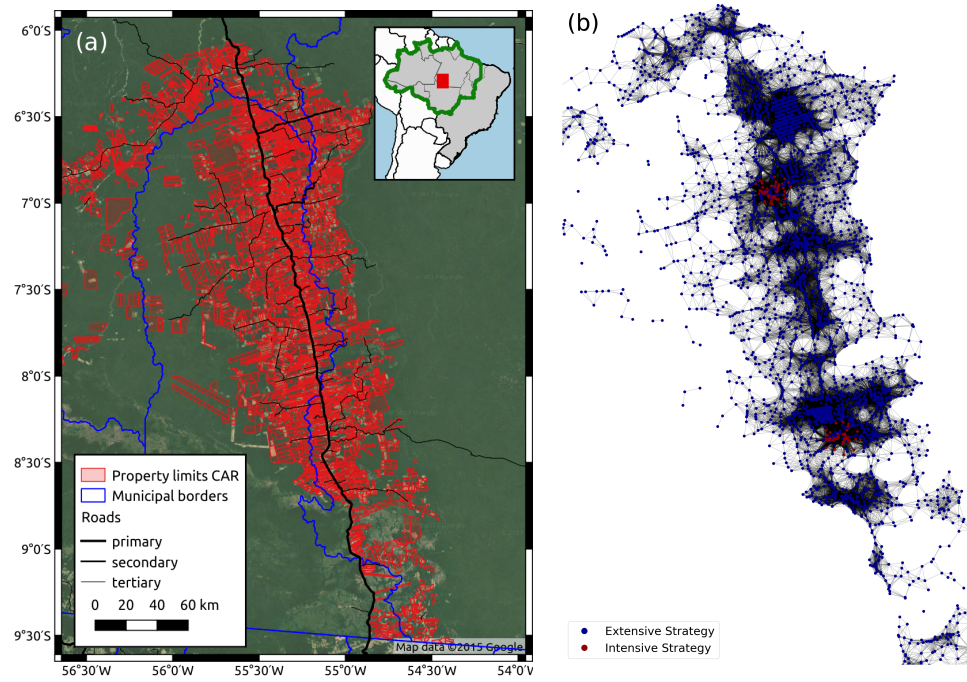


Figure 4.5.: (a) Map of the study region with property limits from SICAR (red), municipality borders (blue) and roads (black). The data is plotted over a satellite image of the region. The inset shows the location in Brazil (grey) and the Brazilian legal Amazon (green line). (b) Geographic neighborhood network derived from this data. Each node represents a property. The color of the nodes depicts the distribution of initial strategies.

log-normal distribution with mean 200 and standard deviation 100 Brazilian Reals (BRL) per ha of property area are allocated to the ranchers.

The model framework was applied to a region around Novo Progresso in the Brazilian Amazon. The region is characterized by strong deforestation in recent years, especially along the highway from Cuibá to Santarém (BR-163). Between 2000 and 2016, the average deforestation on the SICAR-registered properties was 9.5 ha/a with an average property size of 563 ha. In total, 28% of the forest area on registered properties has been cleared (own calculations using PRODES 2018).

Property data from the national land registry (SICAR, 2018) was used to get a representative heterogeneity of property sizes and construct different neighborhood networks. One problem of the SICAR data is that it is incomplete and contains unsettled land claims, which result in overlapping properties. To avoid inconsistencies, properties with large overlap were removed. Figure 4.5(a) shows the municipality of Novo Progresso and its adjacent municipalities as well as the limits of properties in the SICAR data.

The network was constructed by connecting all properties (nodes) closer than a

Table 4.2.: Description, symbols, and values of parameters in the presented ABM. Where applicable, ranges in the literature for the parameterization with the corresponding sources or own calculations are given.

parameter	symbol	model value (default)	unit	sources and comments
deforestation cost	c_D	1500	BRL*/ha	difference of FGV land prices (pasture - forest): 1000 - 3000 BRL/ha
reuse cost	c_R	500	BRL/ha	
pasture maintenance cost	c_m	150	BRL/ha	IMEA (2018): 20 - 30 BRL/@ = BRL/(15kg)
intensification cost	c_I	500	BRL/ha	
beef price		6	BRL/kg	SEAB (2018): 50 - 100 BRL/@
beef weight at selling		500	kg	Tab. 4 in Pacheco and Poccard-Chapuis (2012): 470 - 520 kg
initial cattle price	$p_c(0)$	3000	BRL/head	beef price \times weight at selling
slaughter age	T_p	3	years	Tab. 4 in Pacheco and Poccard-Chapuis (2012): 2.5 - 3 years
average stocking rate	l_{ext}, l_{int}	0.8, 1.6	head/ha	Tab. 3 & 4 in Pacheco and Poccard-Chapuis (2012): 0.5 - 2.0 head/ha
saving rate	s	0.25		average gross saving rate: 0.2-0.3
natural recovery parameter	r_n	0.013	1/year	corresponding to a half-life of about 50 years (Poorter et al., 2016)
regeneration of soil quality of secondary vegetation	r_S	0.06	1/year	corresponding to a half-life of about 10 years (Davidson et al., 2007)
parameter of pasture degradation	β	0.15	1/head/year	corresponding to a half-life of 3 - 4 years for degradation (Costa, 2012)
productivity of pasture after deforestation	q_d	1	arbitrary units (a.u.)	determines scale
threshold on q for abandonment	$q_{\theta a}$	0.2	a.u.	
relative deforested, abandoned and reused areas	$D/X,$ $R/X,$ A/X	0.05	relative area	for deforestation, estimations with PRODES (2018) yield 0.08
maximum relative pasture for extensive strategy	p_{max}	0.5	relative area	
timeperiod for investment decisions	T_{rec}	7	years	information from personal interviews (E. Dalla-Nora): 5 - 8 years
management effort	M	1.5	a.u.	
maximal credit for intensification	k_{min}	200	BRL/ha	
imitation rate	λ	0.001 - 10	1/year	
price elasticity of demand	ϵ	0.1 - 1000		
share of teleconnections	α	0 - 0.1		

* Prices are in 2010 Brazilian Real (BRL)

threshold of 10 km. This resulted in a network with 4012 nodes and an average degree of 81. Furthermore, the model was simulated using geographic networks that have a proportion α of links replaced by random links. I call these links teleconnections because they are independent of the spatial embedding of the network and therefore represent social interactions over distance. Figure 4.5 (b) shows an example network constructed from the property data. For the model simulations, the initial strategies are set as follows: all properties start with the extensive strategy except the ones within a range of 10 km from the major cities, which start with a 50% probability with the semi-intensive strategy. This is motivated by the observation that intensification in agriculturally consolidated areas and areas around cities tend to consolidate faster (Barretto et al., 2013). The colors of the network nodes in the figure indicate initial conditions for the agents' strategies.

Having introduced all model components, the model simulation proceeds in the following sequence: First, the agents make decisions based on the previous state of their environment and their economic situation, as explained in Secs. 4.2.3 to 4.2.5. Second, based on the previous state and the decisions, the system evolves according to the environmental dynamics (Sec. 4.2.1) and produces economic outcomes for the agents (Secs. 4.2.2 and 4.2.7). Finally, the strategy imitation and update as described in Sec. 4.2.6 takes place and the sequence repeats.

4.3. Model analysis and results

The previous section introduced the model design and illustrated the land-use dynamics of single ranches resulting from the two different land management strategies. This section discusses system-level outcomes for model simulations with interacting agents.

4.3.1. System-level dynamics

For parameter settings with a high imitation rate λ and high elasticity of demand ϵ , the initially small number of agents with a semi-intensive strategy increases over time until almost all agents use this strategy. This happens because the increase in produced cattle does not decrease the revenue per area to ranchers significantly. Further deforestation allows more cattle to be raised and thus increases the income, which can be reinvested to deforest more.

Fig. 4.6 shows the key variables of an ensemble of model runs with such a parameter setting (the other parameters are given in Table 4.2). The shaded ranges indicate the variation of variables due to different realizations of the stochastic processes of the model. Panel 4.6(a) displays the average areas on properties specifying the three different land-cover types pasture, forest, and secondary vegetation. Most of the forest is already deforested and converted to pasture in the first 30 to 40 years of the simulation. Panel 4.6(b) plots the development of the average pasture and secondary vegetation productivity $\langle q \rangle$ and $\langle v \rangle$ as well as the average savings of agents $\langle k \rangle$. After an initial peak in pasture productivity stemming from newly deforested pastures

with a high initial productivity, q drops because of ongoing pasture degradation. Later, it increases as more and more agents use pasture management to improve their pasture productivity. The productivity of secondary vegetation is initially low, but increases as the soil regenerates. The agents' savings are low at the beginning and accumulate at the end of the simulation as many agents have already deforested all of their area and cannot invest in more pasture. Panel 4.6(c) shows the fraction of ranchers that adopted the semi-intensive strategy. The fraction of semi-intensive ranchers increases rapidly, because they have the possibility to borrow money for intensification. If this option is not available, they first have to accumulate the savings to cover intensification costs, which slows down the increase (see Fig. B.2). For higher imitation rates and higher cattle prices, this fraction increases more rapidly. Finally, Panel 4.6(d) plots the evolution of the cattle price p_c and produced cattle quantity Y .

For comparison, Fig. 4.7 displays the results of model simulations with similar parameterization except for a lower imitation rate and lower elasticity. Here, one can observe that because of the low imitation rate, the number of ranchers with a semi-intensive strategy increases very slowly (see Fig. 4.7c). This leads to the abandonment of degraded pasture and an increase in secondary vegetation (Fig. 4.7a). Furthermore, the low price elasticity of demand leads to a strong reaction of prices to increasing production at the beginning of the simulation, as a comparison of Figs. 4.6 and 4.7 in panels (d) illustrates. As the pastures degrade and production goes down, the price recovers towards the middle of the displayed simulation time. At the end of the simulation, prices decrease again because intensification sets in and cattle production increases. In the long run, the lower revenues lead to less savings (Fig. 4.7b) and thus slow down deforestation, as Panel 4.7(a) illustrates.

A formal analysis of the asymptotic dynamics of the model is difficult because the system is very heterogeneous and depends on stochastic influences. Long-term simulation results suggest that there are (quasi) stable states or cyclic asymptotic dynamics, depending on the parameter regime. They are only reached after long transients (several hundred years) as an effect of the slow forest recovery. This is why I did not analyze them in detail. Moreover, the model is designed to investigate deforestation, which by definition has no net effect on land-use shares in equilibrium.

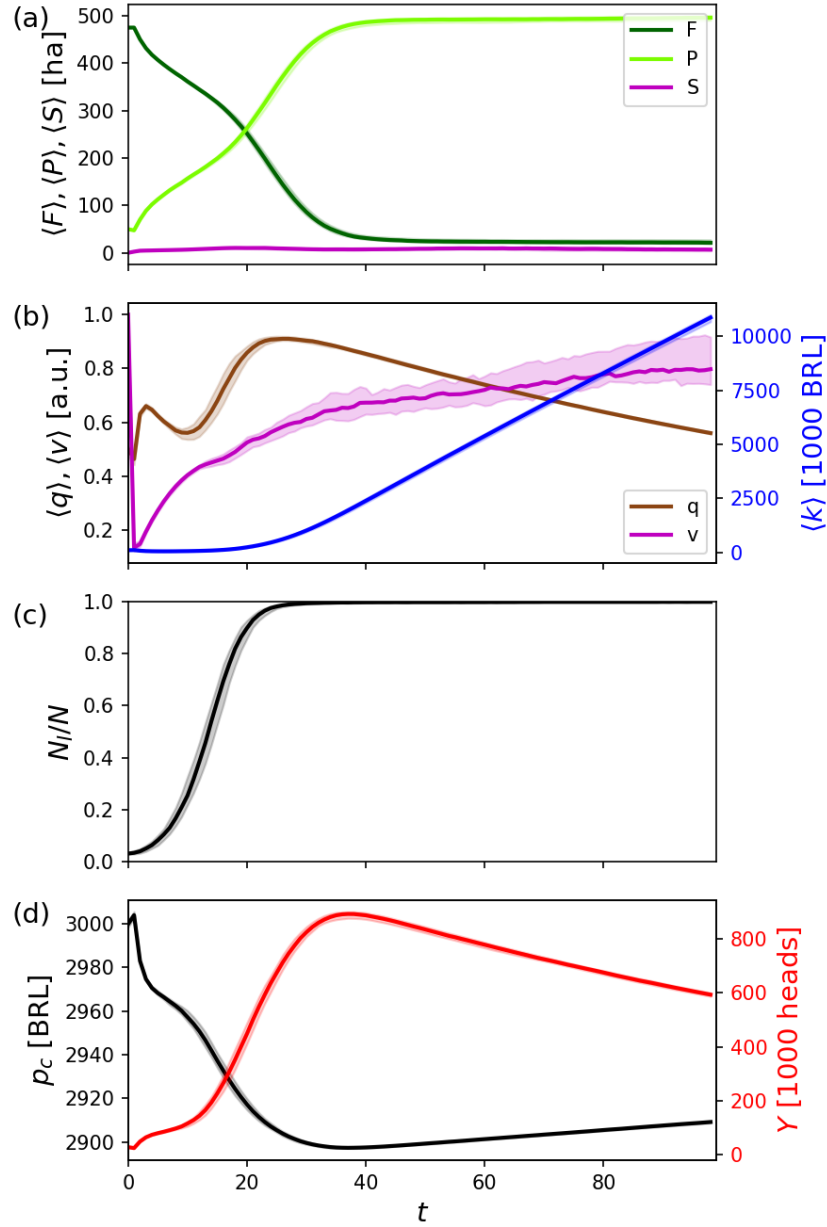


Figure 4.6.: Mean state variables of agents interacting on a geographic network with high imitation rate ($\lambda = 1$), high price elasticity ($\epsilon = 100$), and some teleconnections ($\alpha = 0.02$): (a) mean areas (forest, pasture, secondary vegetation), (b) mean pasture productivity and savings, (c) ratio of ranches with the semi-intensive strategy (red nodes in Fig. 4.5), and (d) price and quantity of produced cattle. The thick lines are the respective ensemble median and the shaded areas around them indicate deviations between different model runs due to stochasticity (5th to 95th percentile).

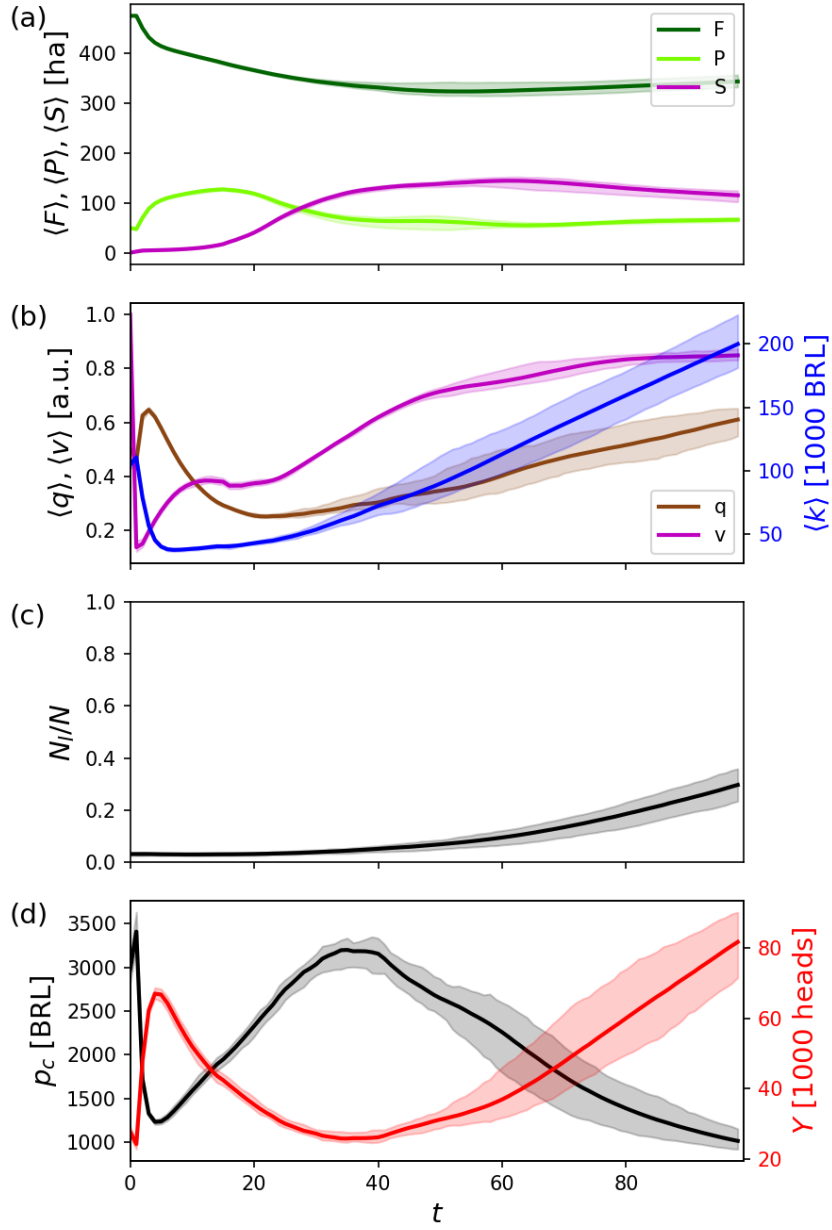


Figure 4.7.: Mean state variables of agents interacting on a geographic network with lower imitation rate ($\lambda = 0.1$) and elasticity ($\epsilon = 1$). The shown variables are the same as in Fig. 4.6.

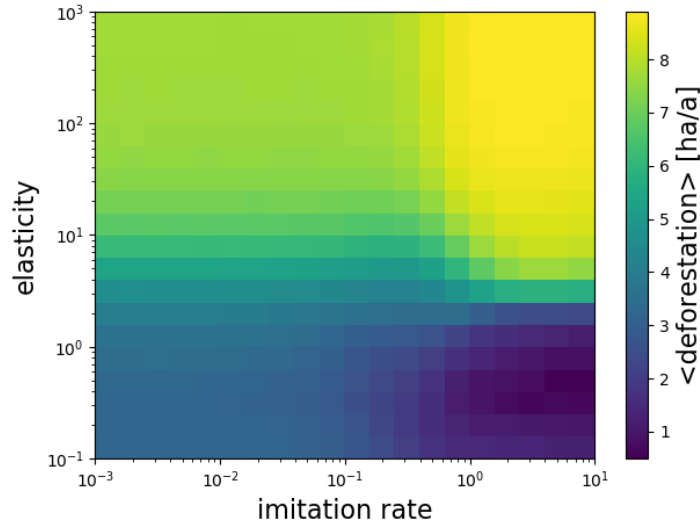


Figure 4.8.: Average deforestation per year and property depending on price elasticity and imitation rate. Parameters are given in Table 4.2 and the initial conditions are based on deforested areas in the study area by 2000.

4.3.2. Parameter analysis

Some model parameters, especially those regarding the social network as well as the decision functions, can hardly be determined empirically because there is no data available (see Table 4.2). Therefore, I present here an analysis of how model results depend on specific parameters. This is also interesting because many of the parameters are presumably not stable over time. An analysis of how transient model trajectories depend on parameter changes can thus illustrate how trends in external drivers of the system might influence model outcomes like deforestation rates. In the following, I investigate properties of the transients of the simulation outcomes and not the asymptotic model behavior.

In Fig. 4.8, the average deforestation is plotted depending on the elasticity of the cattle demand function as well as the imitation rate (both on a log-scale). The deforestation is averaged over the first 50 years after model initialization because this is the period in which most of the deforestation happens (see Fig. 4.6). The results match with observed mean deforestation rates on properties ranging between 3 and 20 ha/year. The figure shows that for low imitation rates and elasticities, the average deforestation is in the medium range of 3-4 ha/year. For low elasticity, this decreases with a higher imitation rate, which is associated to faster intensification. For a high elasticity of demand, this relationship is reversed: A higher imitation rate even increases the already high deforestation rate.

If there are high intensification costs and agents do not have access to credit, the intensification under high imitation rates is hampered. Therefore, such conditions

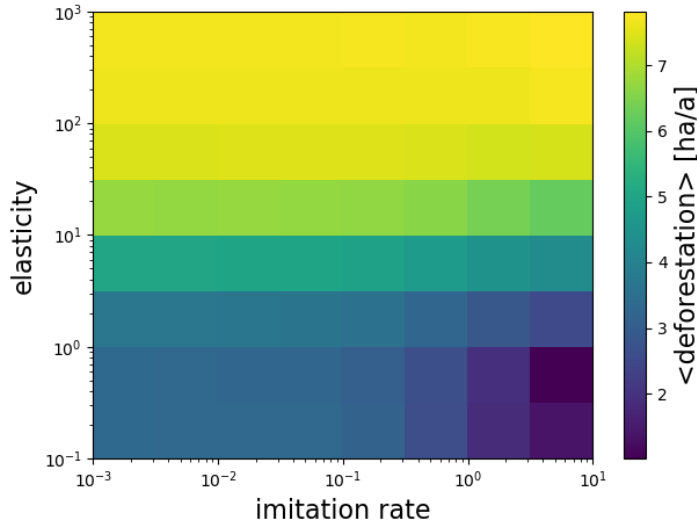


Figure 4.9.: Average deforestation per year and property depending on price elasticity and imitation rate without the possibility for agents to access credit for intensification. Parameters as in Table 4.2.

will not result in an increase of deforestation under high imitation rates, as illustrated in Fig. 4.9.

I also tested other variations of parameters, as indicated by the ranges in Table 4.2. The tested parameter ranges influenced the results quantitatively, but did not change the model dynamics or dependencies relevant for the conclusions of this analysis in a qualitative way. For instance, Fig. 4.10 displays the dependence of deforestation outcomes on the parameter determining the relative areas that agents can deforest in each year. The figure clearly shows that the variation of this parameter preserves the general property that under high elasticity increasing imitation rates lead to higher deforestation outcomes.

The results discussed here are properties of the transient dynamics of the system, not some equilibrium or steady state. Therefore, they depend on the initial conditions of the system, especially on the initial pasture areas, pasture productivity, and savings. I tested the dynamics for different settings of initial conditions and found that for high elasticity an increase in imitation rates does not reduce deforestation rates.

4.3.3. Network effects

The last section focused on the influence that certain parameters and initial conditions have on the model outcome. This part investigates the influence of the topology of the underlying neighborhood network. To account for long-range social ties (i. e., family and friendship relations independent of geographic distance), I tested how the spreading process on the social network changes when a fraction of local links is

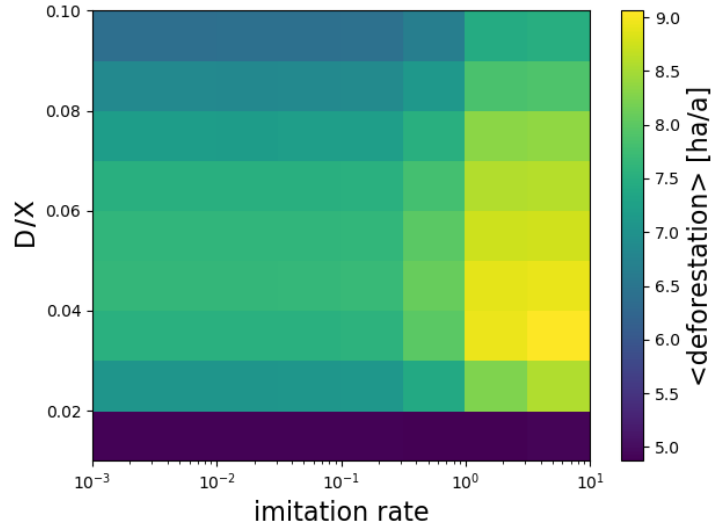


Figure 4.10.: Average deforestation per year and property depending on the parameter D/X describing the relative area that can be deforested in one year and imitation rate λ . Parameters as in Table 4.2 with $\epsilon = 100$.

replaced by teleconnections, i. e., random links that are independent of the spatial embedding (cp. Sect. 4.2.8).

For random initial conditions with a spatially uniform distribution, the spreading does not change strongly when replacing a fraction of local connections with teleconnections. With initial conditions for which ranches with semi-intensive strategies are spatially concentrated (e. g., around local cities or main roads), the additional teleconnections accelerate the spreading of the strategies considerably. Under parameter settings where the semi-intensive strategy is favored, the intensification process is therefore accelerated by the introduction of teleconnections.

Figure 4.11 displays the average deforestation rate depending on the share of teleconnections in the network and the imitation rate for initial conditions with a geographically concentrated strategy distribution, corresponding to clusters of semi-intensive ranchers near cities. We can see that for medium imitation rates, the teleconnection share has an influence on the outcome. The figure and further analyses of the dependence of model outcomes on network parameters suggest that the influence of the network topology on the deforestation outcome is small compared to other effects in the model. In the figure, we can see that adding teleconnections is equivalent to rescaling the imitation rate (or its inverse, the time scale). This rescaling depends on parameters in the models that determine the relative profitability of the different land-management strategies. For comparison with Fig. 4.6, a trajectory of model simulations without teleconnections is displayed in Fig. B.3. It shows that a small fraction of ranchers do not adopt the semi-intensive strategy at all, because

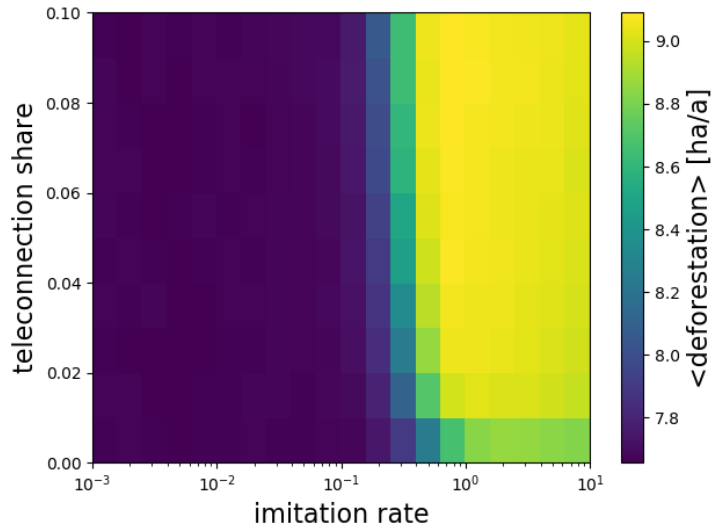


Figure 4.11.: Average deforestation per year and property depending on teleconnection share α and imitation rate λ . Parameters as in Table 4.2 with $\epsilon = 100$.

they cannot reach the nodes in the network that initially start with the semi-intensive strategy.

In addition to the network construction as described in Sect. 4.2.8, I also tested a method for network construction that links nodes with a probability that decays exponentially with distance (Waxman, 1988). This resulted in changes in the network structure because the threshold on the distance was replaced by a characteristic length for the decay. It did not change model outcomes in a qualitative way (see Fig. B.4).

4.4. Discussion

The analysis showed that a stylized model including a few feedbacks and representing the heterogeneity of agents yields rich non-linear dynamics. The model design implies that only price effects, limited access to credit, high costs for investments, and constraints on decision making impede total deforestation. For the chosen assumptions, parameter settings, and initial conditions, the model showed that deforestation can only be curbed by intensification if price elasticity of demand is high. This results in the local cattle market saturating at some point. The main result of this chapter is therefore that intensification can reduce deforestation rates only under very specific conditions.

The elasticity in the model can be interpreted as a measure for the integration of the local cattle market into national or international markets. If markets are well connected to bigger markets, the prices will not be affected much by changes in locally

produced quantities but rather by external price fluctuations. Such fluctuations are not the focus of this study. With ongoing globalization and expansion of infrastructure in the Amazon, the elasticity of demand of local markets will probably rise such that markets will not easily saturate.

The share of teleconnections in the network can be interpreted similarly: with ongoing technical progress, the interaction between ranchers that are not located in the same neighborhood increases. Yet, the model results suggest that this only has a minor effect on the deforestation outcomes. Furthermore, if the costs for intensification are high, limitations on the availability of credit hamper the increase of deforestation in the model. This may reflect the success of policies limiting access to agricultural credits in municipalities with high deforestation rates (Assunção et al., 2013).

In Brazil, conservation policies like the extension of legal reserves and the monitoring and sanctioning of deforestation activities have reduced deforestation considerably. Law enforcement makes illegal deforestation riskier and impedes actors from accessing state aid, for instance subsidized loans. But current legislation provides low incentives for full compliance, especially regarding reforestation (Azevedo et al., 2017). Another way of reducing deforestation is the enforcement of compliance with environmental legislation through supply chain monitoring. The internationalization of beef (and soy) markets has increased pressure on producers to certify that products were not produced on (recently) deforested lands (Nepstad, Stickler, and Almeida, 2006). Such industry efforts (beef and soy moratoria) were probably one of the reasons for the decline in deforestation during the late 2000s (Nepstad et al., 2014). However, meat processing industry in Brazil is highly concentrated in the hands of a few companies (Merry and Soares-Filho, 2017) and the meat scandal in 2017 heavily questioned the reliability of certification standards.

Proposed measures to lower deforestation by fostering land-use intensification have been debated as an alternative. The results of this study suggest that anti-deforestation policies only aiming at intensification of cattle ranching will not have the desired result if they are not accompanied by measures that limit the agents' access to new land. Merry and Soares-Filho (2017) convincingly argued that intensification of cattle ranching will be the result of conservation efforts rather than the cause of lower deforestation and better conservation of forests. This is supported by the obtained results of the model.

An important issue for the design of future anti-deforestation policies is the huge heterogeneity of actors in frontier development. The roles of various types of agents with respect to deforestation outcomes changes as a response to new policy implementations and their effectiveness. Recent studies comparing the contributions of small-holders and large land-owners found opposing trends, depending on the time and location they focused on (Godar, Tizado, and Pokorny, 2012; Godar et al., 2014; Richards and VanWey, 2015). For example, large-scale ranchers, who drive land concentration in more consolidated areas, are susceptible to other incentives than small-holders in remote areas, mainly involved in subsistence land use. To investigate

the different effect of intensification policies and economic drivers on this heterogeneity of agents is a challenge for future modeling studies.

In general, development and environmental policies for the Amazon have to face the various trade-offs between social and environmental issues. Cattle ranching remains an important source of income for land holders in the Amazon. As the demand for cattle products is increasing world-wide (Thornton, 2010), ranching provides an important economic perspective for the region. Policies have to guarantee that local incomes are maintained or increased while conserving the ecosystems. Therefore, it is essential that they can anticipate the multiple feedbacks in the system that could undermine the effectiveness of policies. It remains an open question how cattle ranching in the Amazon will become an environmentally and socially sustainable economic activity in the long term, with or without intensification.

From a methodological perspective, the model analysis in this chapter indicated that the exact trajectories depend on the parameterization of the implemented decision processes and initial conditions. The decision rules used in this model are derived from a survey of the literature and are tuned to reproduce observed land-use patterns in the region. However, there are no empirical studies on the motives, goals, and decision procedures of agents, which makes it difficult to construct sound decision functions. Further research in this direction is needed to improve the validity of results, especially the collection of evidence on how agents in frontier regions make decisions about land use. Furthermore, there often remain many indeterminacies when deriving decision rules from empirical observations even if plenty of data is available. This gap can be bridged by comparing different decision making strategies of agents in a model with empirical data, for instance using inter-temporal or myopic optimization, satisficing, and individual learning approaches. Separating between single intensification practices and techniques would furthermore result in a characterization of intensification as a continuous process, helping to answer for instance the question which level of intensification would be individually and socially optimal.

Two features which are not captured in the presented model are the land market and environmental problems associated with intensified cattle ranching such as nitrogen pollution and water usage. Further research should aim to include such processes to identify agricultural practices that are both economically viable and sustainable over long time scales.

4.5. Summary

This study presented and analyzed a new agent-based model (ABM) that conceptualizes the intensification of cattle ranching as a socially mediated process. This approach shed light on the interplay between ecological dynamics, economic conditions, decision making of agents, and interactions on a social network. I analyzed the model dynamics applying them to a frontier region with recent deforestation and using data sets on land properties (SICAR) and deforestation (PRODES) to initialize and parameterize the model. I showed how even from very stylized assumptions about

these dynamics, a rich non-linear behavior arises at the system level which can be explained by the various feedback loops between them.

In particular, I highlighted the effect of the imitation rate and price elasticity of demand for cattle in the model. The model results indicate that higher imitation rates, which lead to faster intensification, can only reduce deforestation in a market that saturates. On the other hand, under conditions of less responsive prices, faster intensification can even lead to higher deforestation. The presented model shows these effects on a regional scale but similar rebound effects have been discussed for the global food system (Lambin and Meyfroidt, 2011).

The land-use system in frontier regions is a complex system of various types of heterogeneous agents and a highly dynamic environment, shaped by social, economic, and ecological drivers of deforestation. The presented model is a first step towards including local social interaction into models of land-use change in the context of tropical deforestation. Future work with agent-based models could focus on evaluating the effectiveness and resilience of anti-deforestation policies accounting for heterogeneities of actors in the deforestation process (Godar et al., 2014). This can relate for example to the effects of obligatory registration with SICAR and the new market for forest certificates (Azevedo et al., 2017; Soares-Filho et al., 2016).

ABMs are a powerful tool for evaluating such policies because they can represent heterogeneities of agents and account for the various feedbacks in the system. Thereby, they might help developing an economic perspective for the region that provides improvements in livelihoods while reducing deforestation.

Chapter 5.

Conclusion

This thesis applied complex systems methods for data analysis and modeling to social-ecological systems, especially to land use in the Brazilian Amazon. When applying such methods, modelers have to account for the specificities of social dynamics, as I showed in Chapter 2. I presented two different applications: First, I used land-cover data to identify patterns of land-use change and to project the dynamics into the future. Second, I developed and analyzed an agent-based model of Amazonian cattle ranching. In the following, I will first summarize and discuss the main results of the three parts of this thesis, and then give an outlook on questions for future research.

5.1. Summary of main contributions

Modeling co-evolutionary human-nature interactions

Theories of human decision making and behavior are needed to account for the various feedback loops between social and ecological dynamics that dominate social-ecological systems. Chapter 2 reviewed modeling approaches to describe human decision making and behavior based on an extensive literature review, published in Müller-Hansen et al. (2017b, P1). The guiding research question of this chapter concerned the appropriateness of modeling approaches to describe human behavior in social-ecological systems. Because there is no single model capturing all important aspects of human behavior and social interaction appropriately, modeling approaches need to be selected from a broad range of options to best fit the specific context of decision making, the purpose of the modeling exercise, and the underlying research questions.

From a complex systems perspective, social systems consist of multiple agents that interact with each other. Their joint behavior and interactions give rise to emergent aggregate phenomena. This perspective led me to propose a systematization of modeling approaches along three key categories: individual decision making and behavior, social interaction, and aggregation of individual behavior and interaction.

Regarding models of individual decision making and behavior, I compared different approaches with respect to their assumptions about agents' goals, restrictions, and decision rules. While rational choice theory assumes that agents optimize over all possible outcomes and follow distinct goals, bounded rationality, heuristic decision making, and learning emphasize the procedural aspect of decision making. Rational

choice theory can describe situations in which agents have access to the relevant information and sufficient time to evaluate different options. Heuristics describe the decision process by simple rules that guide the search for information to make decisions fast. Learning approaches consider step-wise optimization of strategies through exploration and experience in situations of repeated choices.

Second, approaches to model social interactions focus either on the type of interaction or the structure of interactions in a group of agents. Regarding the first, I introduced strategic interactions as modeled by classical game theory, which assumes agents with high rationality, evolutionary approaches, which assume that the prevalence of a strategy changes according to its relative success with respect to competing strategies, and social influence, which captures different processes in which agents influence each other's attributes like opinions, values, and preferences. These types of interactions often do not occur between all agents in a group but are structured by a social network, which can be formalized as a graph. Graph theory offers tools to study how the structure impacts the interactions on the network. If the network structure also adapts to the dynamics on the network, one can explain feedback dynamics such as social tipping phenomena.

Third, I compared statistical techniques, representative and equilibrium approaches, and their underlying assumptions for aggregating agent behavior and interactions to derive collective dynamics. Equilibrium approaches describe the coordination and aggregation of behavior through price mechanisms and can help to identify under which conditions this leads to desirable outcomes. Techniques for aggregating conflicting preferences imply difficult ethical choices, while voting theory focuses on procedures to possibly reach compromises. The representative agent approach may help to make the description of a system analytically tractable but cannot capture system-level phenomena emerging from the interaction of agents. On the contrary, agent-based models are designed to investigate emergent outcomes but they are difficult to analyze. Methods from statistical physics may help to aggregate the individual behavior and local interactions of groups of agents to allow for an easier analysis and a mathematical explanation of emergent system-level behavior.

I linked the discussed modeling approaches to applications in current models of land use. Here, rational choice and optimization approaches are often applied in equilibrium models of agricultural markets. In recent years, however, agent-based models increasingly explore other ways to model decision making. The model presented in Chapter 4 pursues such an approach.

The chapter highlighted that modelers who aim at describing social systems need to be aware of the fundamental difference between models describing physical, chemical, or biological systems, and models of social systems: the adaptivity and reflexivity of human decision making. This can, in extreme cases, imply that decisions are influenced by the models that are made to describe them, which can lead to self-fulfilling or self-defying prophecies.

Land-cover dynamics and patterns in the Brazilian Amazon

The following part of the thesis looked at land-cover change in the Brazilian Amazon by analyzing patterns and changes in maps derived from satellite data. For this, I developed a novel method by combining Markov transition matrices and cluster analyses to identify spatial patterns of similar land-cover change. Classical clustering algorithms were complemented by community detection algorithms on similarity networks. The guiding question was: How can we identify patterns of land-cover transitions from highly resolved land-cover maps in dynamic regions such as the Amazon?

I used maps of land-cover types from the TerraClass data set to derive transition rates between land-cover classes for subregions in the Brazilian Amazon. The rates were normalized to derive Markov and conditional transition matrices. A clustering analysis was applied to detect similarities and differences in land-cover transitions between subregions. The resulting clusters were mostly coherent in space, indicating that adjacent subregions undergo similar land-use transitions. For transitions from single land-use types, the cluster analysis identified robust and coherent spatial patterns that were interpretable in view of the literature on land-cover change in specific regions of the Amazon. For example, the increasing land conversion to cultivation of annual crops in northern Mato Grosso corresponded to a cluster in that region. Other clusters captured predominant transitions to secondary vegetation or degraded pasture.

However, the clustering algorithms could not identify patterns that were robust along the different methods when comparing transitions between all land-cover types at once. This points at gradual rather than categorical differences between subregions and raises the question if the broad division of the region discussed in the literature (Becker, 2005) still captures main features of current land-cover dynamics.

I also used the theory of Markov chains to project the observed transitions into the future. The projections for the near future showed almost linearly increasing shares of land-use types associated to economic activities in the region, such as pasture and annual crops, but also of secondary vegetation. An investigation of the convergence to a stationary distribution indicated that the associated time scales are in the order of centuries. Such projections can provide insights into how the land-cover ratios might develop if all economic and political conditions remain as they are. However, the informative value of such projections is limited by their inability to capture the response of agents to shifting drivers of land-use change.

Agent-based modeling of deforestation and cattle ranching in the Brazilian Amazon

In the third part of my dissertation, I developed an agent-based model with the aim of investigating the interplay between deforestation and intensification of cattle ranching in the Amazon. I focused on cattle ranching because it is the main direct driver of clear-cut deforestation in the Brazilian Amazon.

The model captures economic, environmental, and social processes in a stylized way. The modeled agents manage their land according to a strategy, either extensive or semi-intensive, which they can imitate from their neighbors on a geographic network. This represents the adoption of management techniques through social imitation of successful acquaintances. The economic outcomes for agents in the model are influenced by natural dynamics such as pasture degradation and their interaction on a local cattle market.

There is a debate in the literature on whether policies that promote the intensification of cattle ranching are effective to reduce deforestation on private lands. This debate motivated the main research question for the model design: Can intensification of cattle ranching in frontier regions of the Amazon reduce deforestation?

The stylized model shows non-linear transient trajectories, suggesting that the answer must distinguish between different circumstances under which increased intensification can or cannot reduce deforestation. Using statistical methods, I analyzed the dependencies of model outcomes like the average deforestation rate on parameters such as the interaction rate of agents and the price elasticity of demand of the local cattle market. The analysis indicated that a reduction of deforestation rates is only possible if the price elasticity is low, i.e., the local cattle market saturates fast enough. Under many other economic and environmental conditions, deforestation is not reduced by faster intensification and sometimes even increases. The analysis of different network types indicated that teleconnections increase the speed of adoption of the new land management strategies. However, the effect is small compared to other parameter dependencies in the model. In summary, the analysis suggests that a one-size-fits-all solution like intensification can lead to very different outcomes and often to rebound effects. Intensification is inappropriate if not accompanied by policies that anticipate these rebound effects.

5.2. Outlook for future research

In this part, I will conclude with some reflections on future strands of research that could follow up the work presented in this thesis.

In general, the review of modeling approaches to human decision making and behavior showed that there are many promising theories and approaches. Some of them are only starting to be applied in models of social-ecological systems. Approaches such as fast and frugal heuristics or Bayesian learning have a huge potential for application in social-ecological models, especially when using agent-based approaches. Future research should explore further how adaptive networks could be used to model social organization from a dynamic or evolutionary perspective, combining for example individual and social learning.

Aggregation techniques such as moment closure are promising techniques to explain mechanisms behind emergent phenomena in social-ecological systems. For detailed agent-based models, it may be difficult to apply these techniques. But stylized models

of systems of heterogeneous agents could be a starting point for such work and computer algebra systems can help to track lengthy derivations and expressions.

The presented data analysis can be expanded to include the two additional time slices of the TerraClass data set that became available after the publication of my work and further data to appear in the future. If such data sets are further extended, they could be combined with socio-economic and demographic data, e. g., from agricultural censuses, to estimate transition rates in dependence of socio-economic parameters. This would allow including the impact of external drivers into Markov-type models.

For the agent-based modeling of deforestation and subsequent land use, there are two promising directions for further research. First, stylized agent-based models of land-use change should complement very detailed models. It is an open question whether the model presented in this thesis can be simplified further while still capturing general properties of the system. Developing the model in this direction might also allow applying statistical aggregation methods to analytically analyze emergent outcomes.

Second, empirical social-science research on deforestation and land management decisions is needed to develop a better empirical basis for decision making functions in agent-based models. Such research should design questionnaires for cattle ranchers with the goal of informing social-ecological models of deforestation dynamics and carry out interviews with ranchers to find out the determinants and rules that motivate their decisions. Such insights would allow representing the heterogeneity between agents regarding their decision making more realistically in models. Including more empirical insights on the decision making of agents would help to anticipate the agents' heterogeneous reactions to policy interventions more accurately.

The proposed directions for follow-up research show that there are still many unknown properties of social-ecological systems in general and the land-use system in the Amazon in specific. This thesis showed that methods from statistical physics help to develop a holistic complex systems perspective on such systems.

Appendix

Appendix A.

Additional material for the analysis of land-cover transitions in the Amazon in Chapter 3

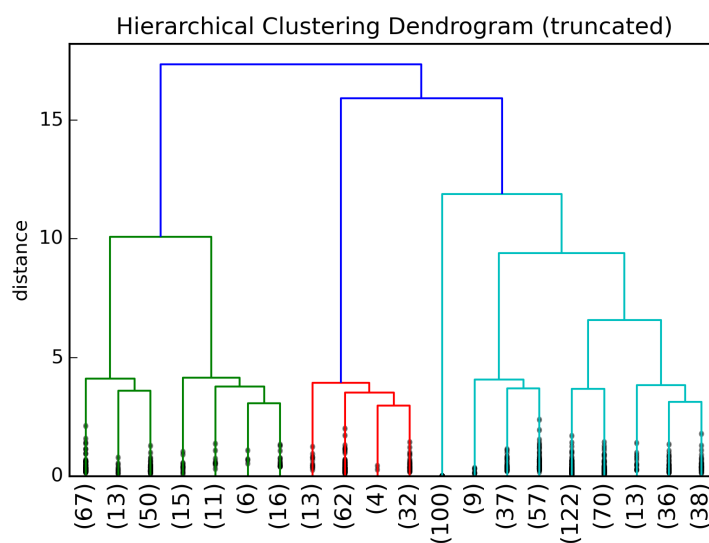


Figure A.1.: Dendrogram showing the distance between clusters of transition matrices for different hierarchies of clustering. The underlying Markov matrices are calculated for Amazon municipalities for the transition from 2010 to 2012.

Table A.1.: Total area of transitions between land-cover classes (numbers according to TerraClass, see Table 3.1) between 2010 and 2012 in km² for the entire region mapped by the TerraClass project.

TC 2010 TC 2012	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16
01	33457	24	0	1	5765	277	407	0	580	5	316	66	0	73	0	121
02	35	3936	0	9	837	479	935	2	1601	50	1120	2	0	241	0	342
03	18	114	4469	12	323	102	63	2	94	9	117	1	0	5	0	13
04	1	19	0	680	107	27	39	6	90	12	28	0	0	17	0	22
05	3871	3549	0	109	270738	25563	17230	286	10679	305	10661	115	0	1290	0	1602
06	369	1243	0	15	22535	10993	7639	20	2936	117	3675	41	0	587	0	662
07	617	1668	0	24	11915	6688	15028	19	2667	184	5365	76	0	1316	0	1161
08	1	1	0	1	15	3	2	16	2	0	3	0	0	0	0	0
09	619	3096	0	47	8664	4099	12040	4	132504	233	8805	187	0	1028	0	1537
10	26	314	0	20	1396	659	564	7	1041	1339	429	3	0	114	0	202
11	629	3984	0	69	17670	7074	8946	9	13251	511	14993	431	0	607	0	961
12	335	9	0	0	242	41	207	0	58	4	137	2093	0	12	0	38
13	0	0	0	0	0	0	0	0	0	0	0	0	953244	0	0	0
14	0	0	0	0	2	0	0	0	0	0	0	0	0	3189252	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	114913	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	4305	0	0

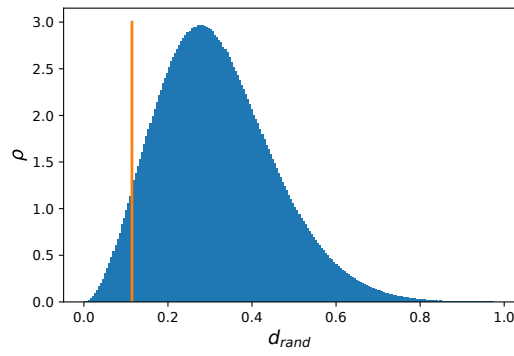


Figure A.2.: Distribution ρ of the difference measure d_{rand} of randomized vectors of dimensionality 4 (blue) and 5th percentile (orange) to determine the threshold for the construction of similarity networks d_{th} . Note that the distribution changes with the dimensionality of the data.

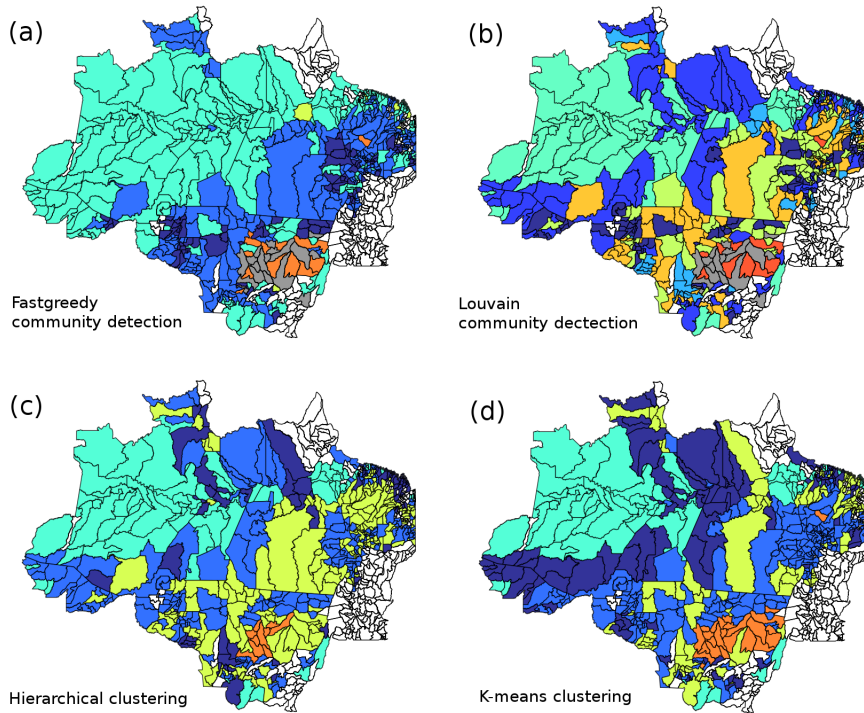


Figure A.3.: Comparison of network (a, b) and classical (c, d) clustering algorithms for transitions from secondary vegetation to other land-cover classes between 2010 and 2012. The (arbitrary) colors indicate municipalities belonging to the same cluster. White regions lack data to estimate the transition matrix, grey regions are not connected to the similarity network.

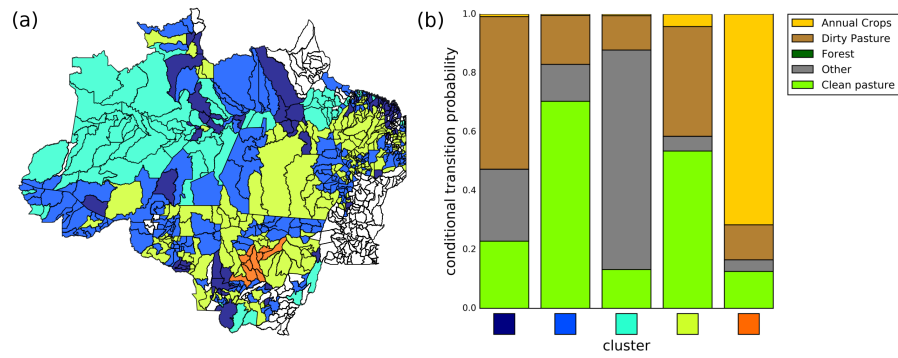


Figure A.4.: (a) Hierarchical clustering as in Fig. A.3(c). (b) Corresponding cluster centroids showing the average conditional transition probabilities of the respective clusters.

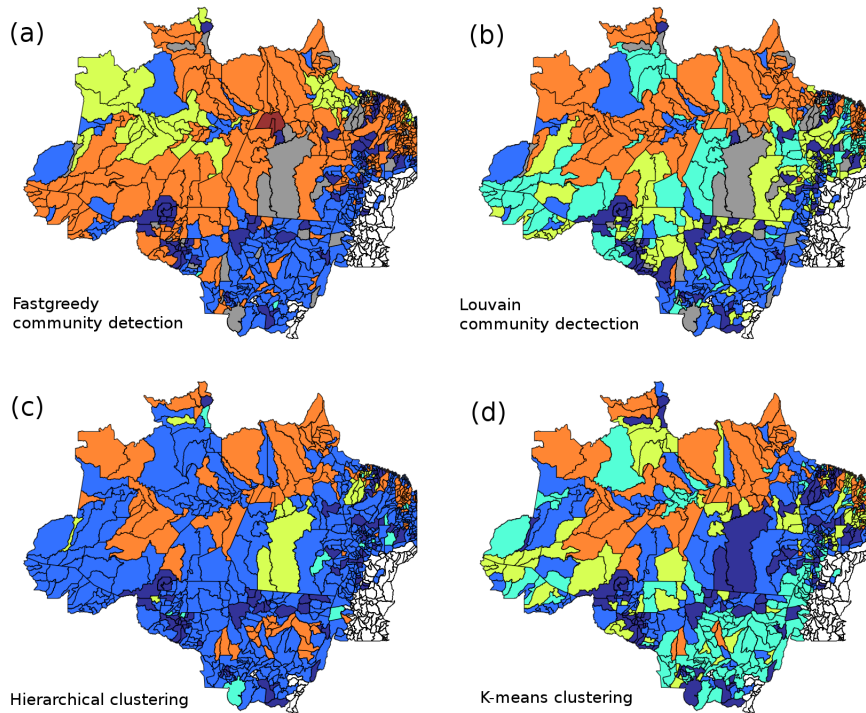


Figure A.5.: Comparison of network (a, b) and classical (c, d) clustering algorithms for the Markov matrices \mathbf{p} between 2010 and 2012. Each cluster is visualized by one color. White regions lack data to estimate the transition matrix, grey regions are not connected to the similarity network.

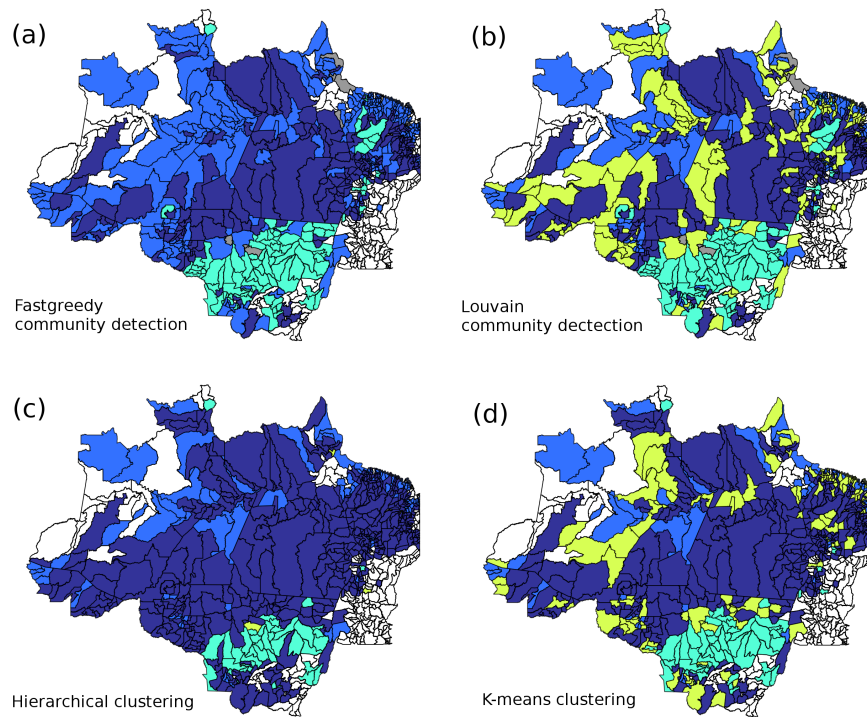


Figure A.6.: The same analysis as in Fig. 7 but with transitions between 2008 and 2010.

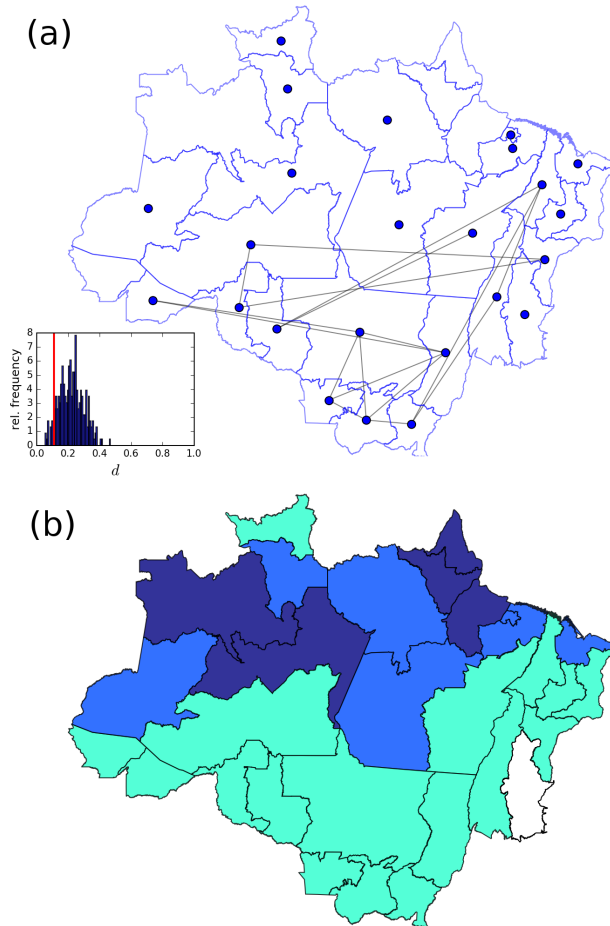


Figure A.7.: Illustration of the clustering with mesoregions as spatial partition for the Markov matrices \mathbf{p} between 2010 and 2012. (a) Similarity network: Because there are only few significant links and only few nodes connected to the network, the community detection is not feasible. (b) Result of the hierarchical clustering with 3 clusters.

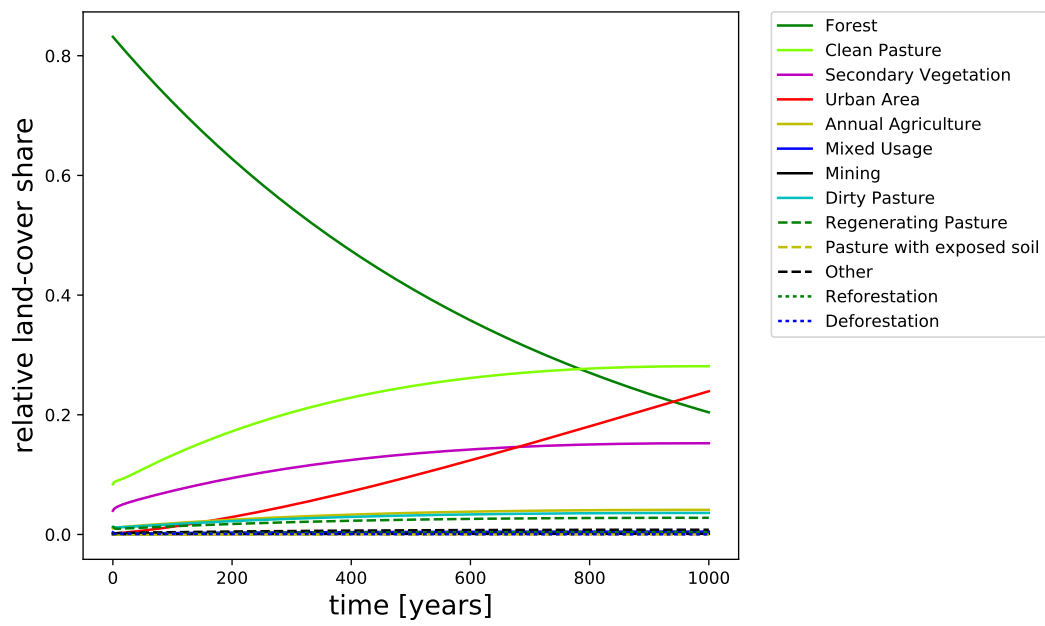


Figure A.8.: Markov model projection with all TerraClass land-cover types (except non-forest, missing data, and water)

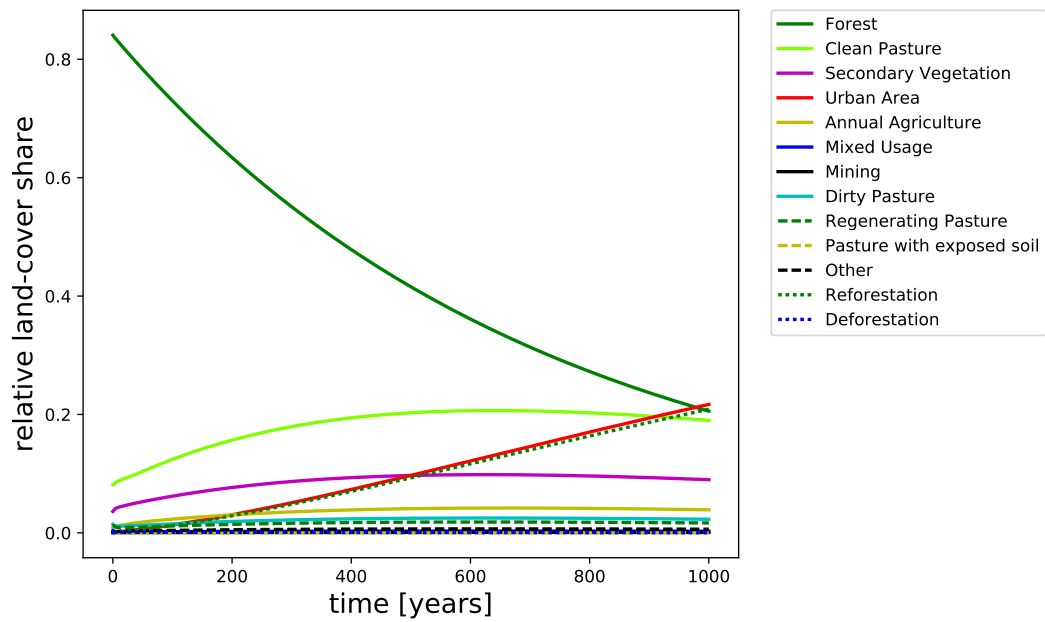


Figure A.9.: Second-order Markov model projection with all TerraClass land-cover types (except non-forest, missing data, and water)

Appendix B.

Additional figures for the analysis of the agent-based model in Chapter 4

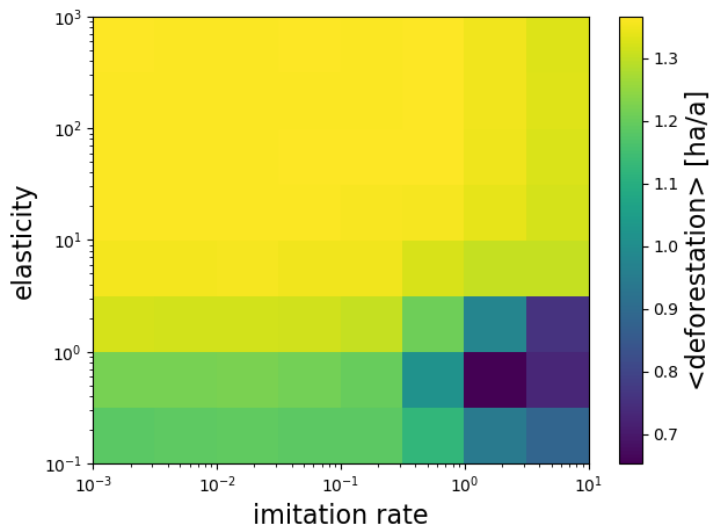


Figure B.1.: Average deforestation per year and property in dependence on price elasticity and imitation rate with only 20% of the properties available for deforestation. This is the share that can be deforested legally according to Brazilian environmental legislation (the Forest Code). Initial conditions correspond to 2000.

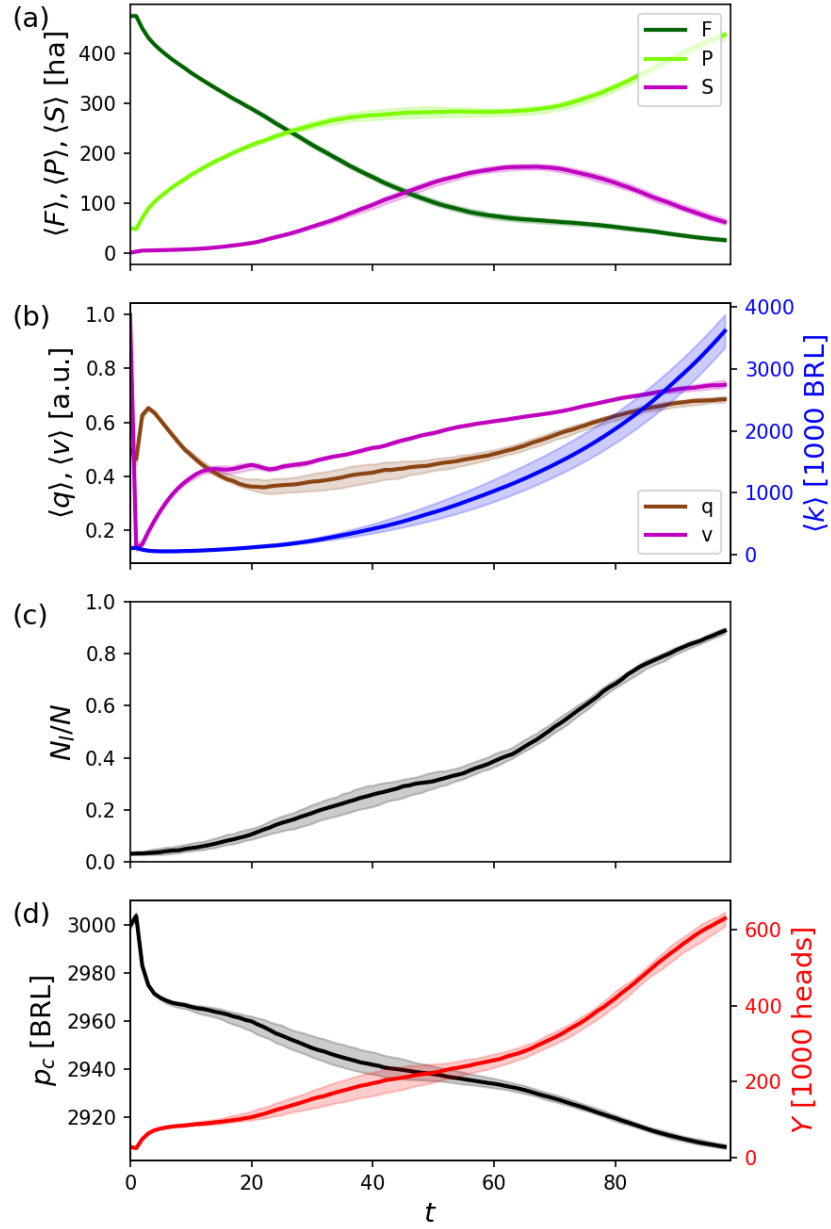


Figure B.2.: Mean state variables of ranches without the possibility for agents to access credit for intensification. All other parameters are the same as in Fig. 4.6 ($\lambda = 1$, $\epsilon = 100$, $\lambda = 0.02$). (a) mean areas (forest, pasture, secondary vegetation), (b) mean pasture productivity and savings, (c) ratio of ranches with the semi-intensive strategy (red nodes in Fig. 4.5), and (d) price and quantity of produced cattle. The thick lines are the respective ensemble median and the shaded areas around them indicate deviations between different model runs due to stochasticity (5th to 95th percentile).

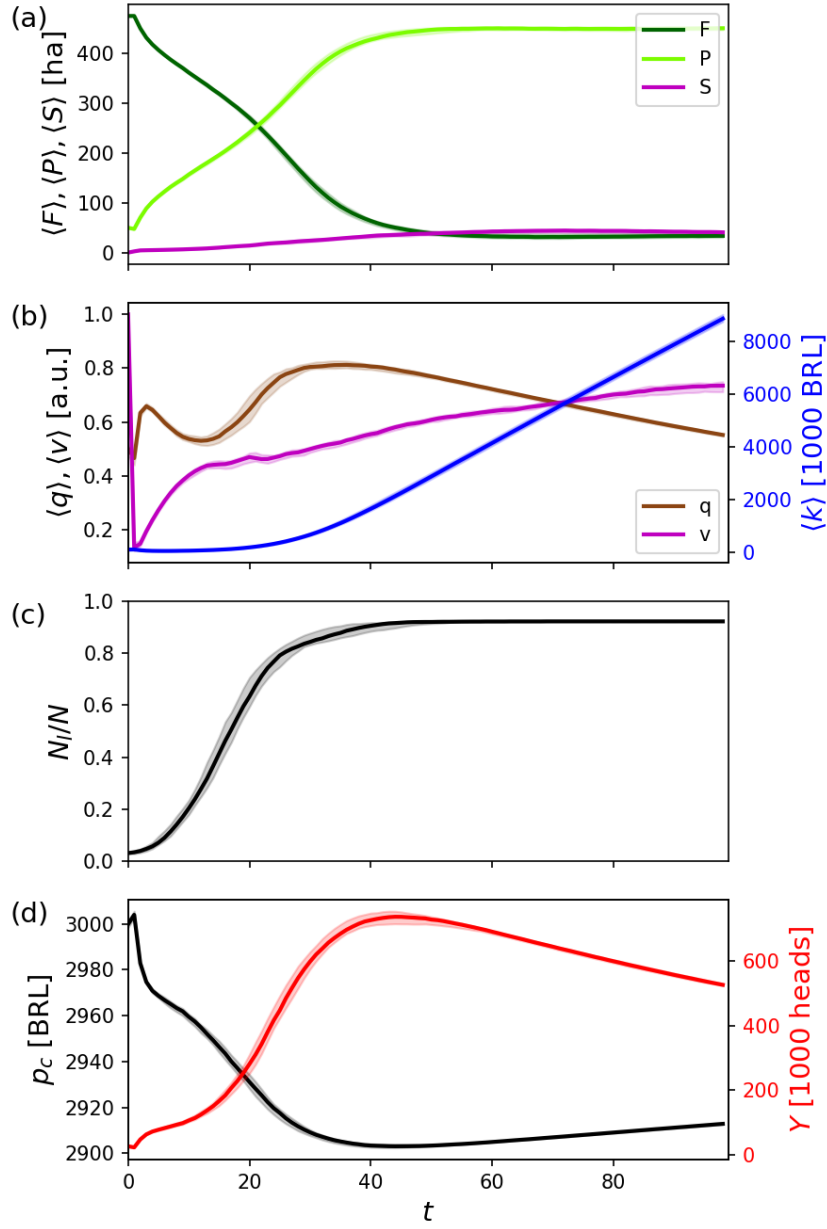


Figure B.3.: Mean state variables of ranches interacting on a geographic network without teleconnections as depicted in Fig. 4.5. All other parameters are the same as in Fig. 4.6 ($\lambda = 1$, $\epsilon = 100$). The ratio of ranches with the semi-intensive strategy in Panel (c) increases more slowly as compared to Fig. 4.6. Furthermore, because not all nodes of the network are connected to the part of the network containing the nodes with initially semi-intensive strategies, not all ranches can adopt the semi-intensive strategy.

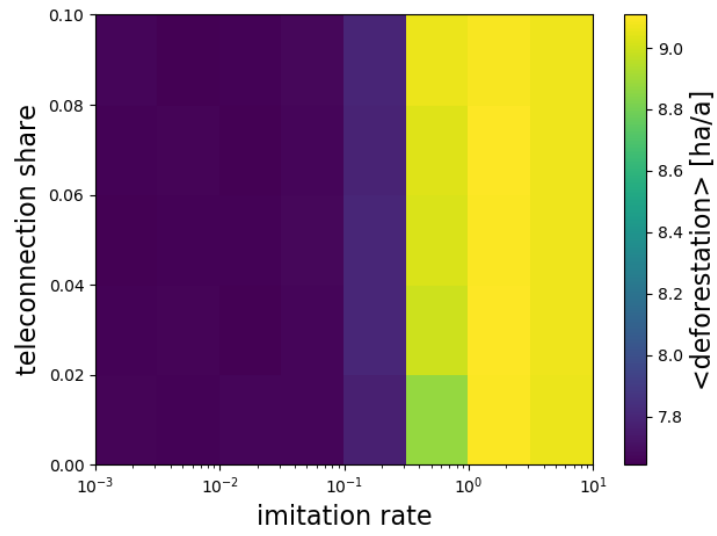


Figure B.4.: Average deforestation per year and property in dependence on teleconnection share α and imitation rate with networks generated by the algorithm proposed by Waxman (1988).

Code and data availability

The code for the data analysis and modeling presented in this thesis is available from the author upon request. Please do not hesitate to contact me. All data used for the analysis is available online and was referenced accordingly.

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Selbständigkeitserklärung

Ich erkläre, dass ich die Dissertation selbständig und nur unter Verwendung der von mir gemäß § 7 Abs. 3 der Promotionsordnung der Mathematisch-Naturwissenschaftlichen Fakultät, veröffentlicht im Amtlichen Mitteilungsblatt der Humboldt-Universität zu Berlin Nr. 126/2014 am 18.11.2014 angegebenen Hilfsmittel angefertigt habe.

Ich habe mich nicht anderwärts um einen Doktorgrad im Promotionsfach Physik beworben und besitze keinen Doktorgrad im Promotionsfach Physik.

Die Promotionsordnung der Mathematisch-Naturwissenschaftlichen Fakultät, veröffentlicht im Amtlichen Mitteilungsblatt der Humboldt-Universität zu Berlin Nr. 126/2014 am 18.11.2014 habe ich zur Kenntnis genommen.

Berlin, den 29. März 2018

Finn Müller-Hansen